Changing Business Cycles: The Role of Women's Employment

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Abstract

This paper proposes that the steep rise in women's labor force participation throughout the 1970s and 1980s, and its flattening out since the early 1990s can contribute an explanation for three puzzling phenomena that have changed the behavior of US business cycles: i) the non-stationarity of aggregate hours in the 1970s-1980s; ii) the decline the cyclicality of output and aggregate hours starting in the early 1980s, known as the *great moderation*; iii) the sluggish growth in employment in the aftermath of recessions starting with the 1991 cycle, referred to as *jobless recoveries*. To explore this hypothesis, we first examine the empirical connection between the changing trend in female participation and the evolution of the cyclical behavior aggregate employment and hours. We then develop and estimate a dynamic stochastic general equilibrium (DSGE) model that allows for gender differences in labor supply and productivity to assess the implications of the changing trend in female employment on the behavior of aggregate variables. We show that the model is consistent with medium run changes in the correlation between output, aggregate hours, and productivity. Based on the estimated model, we find that female specific shocks explain a substantial fraction of the variance of aggregate outcomes, both at the business cycle frequency and in the long run, and assess their role in accounting for the changes in aggregate business cycles. Our results suggest that a DSGE model for the U.S. economy in the post-war period that does not include gender specific shocks to labor supply and productivity is misspecified, and leads to misleading inference on the source of economic fluctuations and on the impact of aggregate shocks. The model with gender specific shocks is consistent with the notion that the increase in female labor supply is strong factor for both the great moderation and jobless recoveries.

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1 Introduction

The rise in women's market work is one of the most notable economic developments in the post-war period in the United States. Female participation rose from 37% in 1960 to a peak of 61% in 1997, and then flattened out since then (figure 1). This phenomenon led to a sharp rise in the share of female hours, contributing substantially to the rise in aggregate hours per person in the US in the 1970s and 1980s. While a large literature has studied the determinants of the rise in women's employment, the implications of this phenomenon for aggregate business cycle dynamics have been left largely unexplored.

This paper proposes that the steep rise in women's labor force participation throughout the 1970s and 1980s, and its flattening out since the early 1990s can contribute an explanation for three puzzling phenomena that have changed the behavior of US business cycles: i) the non-stationarity of aggregate hours in the 1970s-1980s; i) the decline in the cyclicality of output and aggregate hours starting in the early 1980s, known as the *great moderation*; iii) the sluggish growth in employment in the aftermath of recessions starting with the 1991 cycle, referred to as *jobless recoveries*.

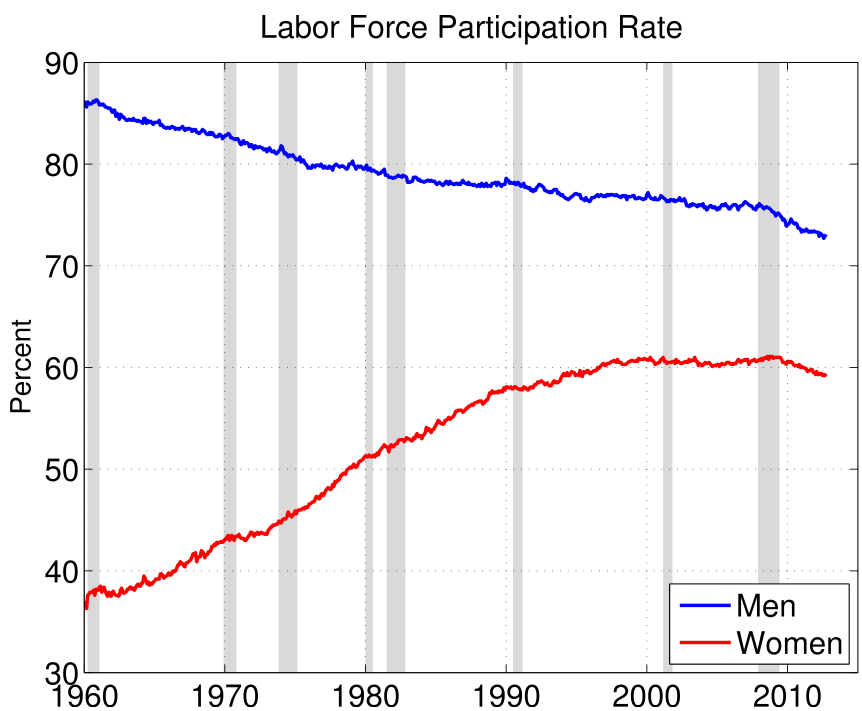


FIGURE 1: Labor force participation rate by gender. Source: Current Population Survey.

The first part of the paper makes the empirical case for this argument. To do so, we use micro data to construct aggregate time series for hours and wages by gender similar to the corresponding aggregates used in business cycle analysis. The resulting labor income shares and hours per worker by gender are displayed in figure 2. Using a series of decompositions and counterfactuals, we empirically assess the role of the changing trend in female employment on the time variation in US business cycles, concentrating on the implications for labor market performance.

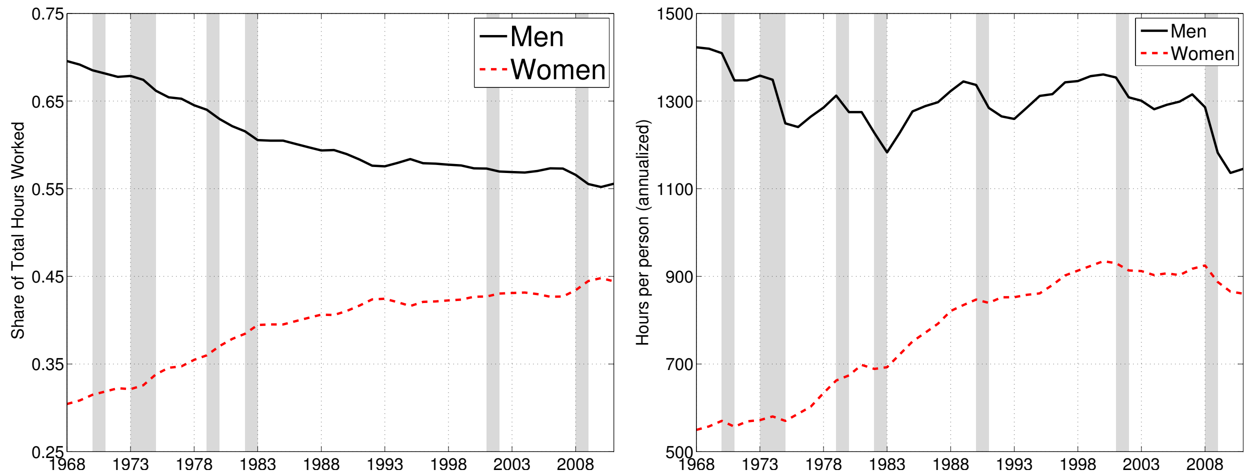


FIGURE 2: Left: The share of hours worked by gender. Right: hours per person. Source: CPS March Supplement.

The second part of the paper develops and estimates a dynamic stochastic general equilibrium (DSGE) model that allows for gender differences in labor supply and productivity to assess the implications of the changing trend in female participation and wages on the behavior of aggregate variables. The model is estimated with yearly data from 1969 to 2011 and its performance is compared to that of a standard real business cycle model with no gender differentiation, estimated over the same period. The model with gender differentiation allows us to decompose the observed patterns in hours worked and the relative wage into components due to demand and supply factors, both in the trend and at the cyclical frequency. This decomposition can provide a useful reference point for the more detailed modeling of the underlying drivers of the increased labor market participation and relative wages of women, and, perhaps most importantly, it allows us to better understand and predict aggregate responses of hours, employment and wages to macroeconomic shocks and government policies.

The key feature of our model is that, unlike in most of the business cycle literature, men and women's hours are not perfect substitutes, and instead enter the production function as a CES aggregate with different marginal productivities, which fluctuate over time. Moreover, we assume that men and women differ in their marginal disutility of labor, both because of different Frisch elasticities of labor supply—a well documented empirical fact—as well as because of a different "taste" for market work, which we model as an exogenous stochastic process. Qualitatively, the model is consistent with the medium run changes in correlation between output, aggregate per capita hours and productivity that started in the late 1970s and comprise some of the forces behind the great moderation, as argued in Gali and Gambetti (2009) [18].

We use standard methods to estimate the model. Since female hours exhibit a strong positive trend up until the early 1990s, when they become stationary, in our estimation we take the period between 1995 and 2004 to correspond to a balanced growth path where only aggregate variables display a trend component, while we allow for gender specific trends in prior years.

We find that the gender specific shocks account for a larger fraction of variance of output, hours and investment than the technology shock at medium and long horizons. By estimating version of the model that exclude the gender specific shocks, we show that the demand shocks, specifically, the preference and government consumption shock, absorb the trend in aggregate hours and wages not captured by the missing gender specific shocks. We also show that a version of the model without gender specific shocks would estimate a decline in the variance of the technology shock starting in the mid 1980s, leading to the conclusion that a decline in the variance of the shock is the main source of the Great Moderation for that time period. However, including the gender specific shocks, there is a decline in the volatility of the cyclical component of these shocks and an *increase* in the volatility of the technology shock. This suggests that the decline in the volatility of the gender specific shocks is the main source of the decline in output and aggregate hours volatility observed starting in the mid 1980s.

Finally, we estimate the model in two separate periods, prior to 1994, when female participation was rising and women's wages were converging rapidly to men's, and 1995-2011, when these two phenomena stopped. We find that the gender specific shocks account for smaller fraction of the variance of aggregate variables and hours in 1995-2011, and the technology and government spending shock explain a larger fraction of the variance of output and hours. Moreover, these aggregate shock display a higher estimated persistence. Thus, technology and government consumption shocks induce larger and more persistent responses in output, investment and hours in the 1995-2011 period. This property of the model is consistent with the slow recovery of output and employment experienced in the 1991, 2001 and 2007-09 recession.

Taken together, these findings suggest that a DSGE model of the U.S. economy for the post-war period that does not include gender specific shocks to labor supply and productivity is misspecified, and leads to misleading inference on the source of economic fluctuations and on the impact of standard aggregate shocks.

1.1 Contributions and Relation to the Existing Literature

There is an extensive literature on the rise in women's market work and the increase in their wages relative to men. Many of these explanations have focussed on the role of technological advances in increasing both the supply and the demand of female labor. On the supply side, Goldin and Katz (2002) [20] show that the diffusion of oral contraceptives reduced the costs and increased the returns to women's education, contributing to a rise in their participation and wages. Greenwood, Seshadri and Yorugoklu (2005) [21] argue that advances in home appliances increased female participation by reducing the time required for home production. Albanesi and Olivetti (2016) [2] show that improvements in maternal health and the introduction of infant formula are key to explaining the rise in participation of married women with children, and the rise in women's education and wages relative to men.[1]

[1] Little work has been done on the flattening out of female participation in the 1990s. Albanesi and Prados (2011) [3] show that the flattening out is driven by a decline in participation of prime age women with college degrees, and

On the demand side, Galor and Weil (1996) [19] attribute the rise in women's market work and the growth in their relative wages to technological innovations that increase the returns to intellectual rather than physical skills, in which women have a biological comparative advantage. Empirical evidence also supports this notion.[2] Rendall (2010) [27] shows that, as job requirements have shifted from more physical to more intellectual attributes, women, who always worked in occupations with relatively low physical requirements, also shifted from occupations with low to high intellectual requirements.

Compared to the macroeconomic literature on the rise in female labor supply and the decline in the gender wage gap, which attempts to spell out the detailed mechanisms that fueled the shift of female labor supply from the home to the market and the technological determinants of the rise in female relative wages, our approach takes as given the differences in productivity and disutility of labor between men and women and focuses instead on quantifying their relative role in producing the observed outcomes. Our estimation procedure, therefore, can be thought of as a device to back out the processes for the relative productivity and disutility of labor between men and women that rationalize both the evolution in female labor supply and of the gender wage gap in the last 40 years. Our results can be then used to examine the link between these phenomena and the changing behavior of aggregate labor market outcomes in the trend and at the cyclical frequency.

1.2 Organization

The empirical motivation for this study is discussed in Section 2. We provide a description of the model with gender differentiation in Section 3 and discuss its main qualitative properties. In Section 4, we present estimation results for the model estimated for yearly data from 1969 to 2011. These preliminary results highlight the importance of the novel features introduced in the environment, namely, the gender specific shocks, to account for the time variation in the business cycle behavior in key aggregate variables.

2 Motivational Evidence

We begin our analysis with motivational evidence relating the changing trends in female labor force participation to the long run behavior of aggregate per capita hours, the great moderation and the emergence of jobless recoveries.

those married to high earning husbands. They identify the acceleration of the rise in the skill premium in the 1990s, and the corresponding sharp rise in top incomes for men, as the main contributor the the decline in the growth of female participation. Fernandez (2012) [15] and Fogli and Veldkamp (2012) [16] explore learning models in which women's participation rises as the perceived costs of women's work fall over time. These learning models also predict a flattening out of the rise in participation at the end of the learning process.

[2]Black and Juhn (2000) [6] argue that the rising demand for skilled workers may have contributed to the rise in participation of skilled women, and to the increase in the fraction of women in professional and managerial occupations, which were traditionally male. Additionally, Black and Spitz-Oener (2007) [7], find that women have witnessed relative increases in non-routine analytic tasks and non-routine interactive tasks, associated with higher skill levels.

2.1 Non-Stationary of Aggregate Per Capita Hours

We first relate the rise in female participation to the non-stationarity of aggregate per capita hours in the post-war period. There is some debate on the stationarity of aggregate hours in the empirical macroeconomics literature, since this property of hours is key in determining their response to technology shocks (see [11] and [12] and [17]) and it is inconsistent with the standard real business cycle model.Figure 2 shows that male hours per capita have been stationary throughout the sample period. In light of the growth in female hours per capita and the rising share of female hours in total hours, it is not surprising that aggregate hours per capita should display trend like growth in the 1970s and 1980s. However, in the period since 1990, when female participation flattened out,[3] female hours per capita also appear to be stationary.

To examine the role of increased female labor supply on aggregate hours, we resort to a simple counterfactual, displayed in figure 3. Hours per capita are calculated as:

$$\frac{H_t^j}{P_t^j} = h_t^j \times w_t^j \times E_t^j / P_t^j, \tag{1}$$

where h_t^j denotes average hours worked per week and w_t^j average weeks worked per year for gender $j = f,\ m$. The evolution over time of each of these components is displayed in figure 4.

The solid black line in figure 3 represents aggregate hours per capita. We impose that share of female hours in the total (Intensive Margin, red dashed line) and the share of female employment (Extensive Margin, blue dashed line) in the total remain constant at their 1968 values and compute the resulting path for aggregate hours. Clearly, the growth in female hours on the intensive margin, and especially the growth in female employment contributed substantially to the trend growth in aggregate hours per capita from the mid 1970s to the mid 1990s. Combined (Both, black dashed line) they can account for virtually all the trend in aggregate hours over that period, making the counterfactual series stationary.

The large contribution of the extensive margin is not surprising, given that employment has registered the largest degree of convergence across genders, as shown in figure 4.

2.2 Great Moderation

The second phenomenon we consider is the Great Moderation, that is the decreased cyclical volatility of several key macroeconomic indicators observed starting in 1984.[4] We show that the reduction the volatility of aggregate per capita hours in absolute terms and relative to GDP can be accounted in part by the rise in the share of female hours during the 1970s and 1980s. Figure 5 reports the trend and cyclical components of female and male hours per capita starting in 1976. As previously noted, there is a strong positive trend in female hours until the early 1990s, and the amplitude of the cyclical fluctuations of female hours is smaller than male hours, especially for the more severe

[3] See [3] for the role of rising inequality in the flattening out of female participation.

[4] See [28] for an excellent review of the evidence.

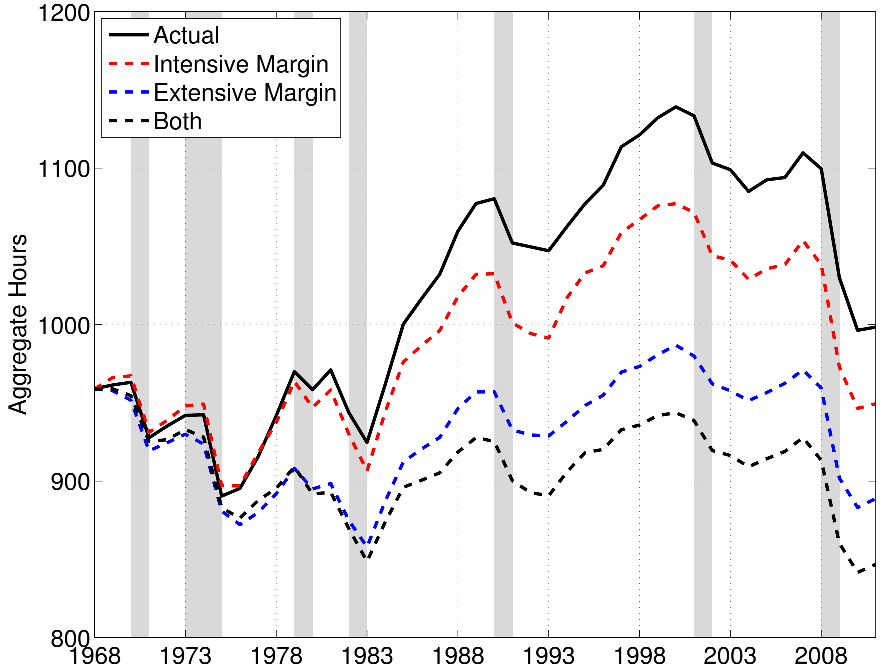


FIGURE 3: Counterfactual evolution of aggregate hours per person. Source: CPS March Supplement.

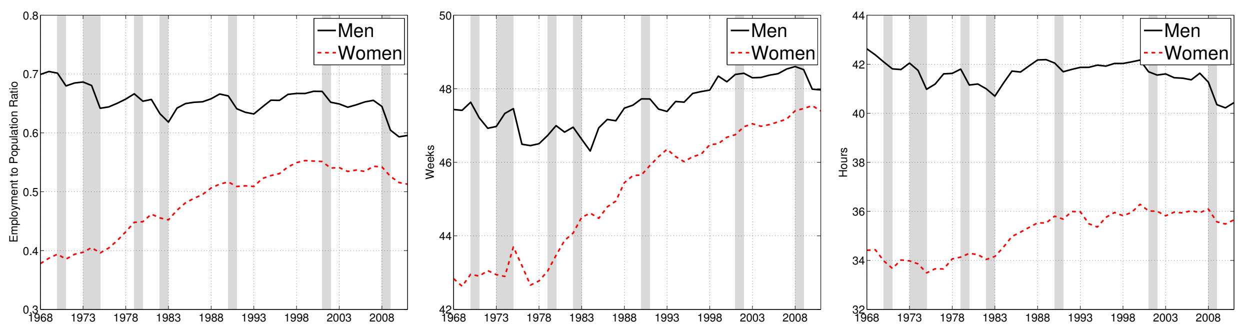


FIGURE 4: Left: Extensive margin, E/P. Center: Intensive margin, average weeks worked per year. Right: Intensive margin, average number of hours worked per week. Source: CPS March Supplement.

recessions. [4] show that the gender difference in the cyclicality of hours and employment can be mostly accounted for by the gender differences in occupational distribution in starting with the 1991 cycle, and by a combination of the occupational distribution and the trend in female participation in earlier cycles. The "added worker" effect is another factor that contributes to the lower cyclicality of female hours. The increase in female participation up until the early 1990s determined a rise in the fraction of female hours, thereby reducing the cyclicality of aggregate hours over this period.

Table 1 presents evidence on the Great Moderation and the possible contribution of the rise in the share of female hours. The bottom panel shows the decline in the business cycle volatility of GDP, aggregate hours and the employment to population ratio in 1985-2005 relative to 1969-1984, which is close to 50% for all these variables. The middle panel reports that in both periods, the business cycle volatility of female hours is just over half of that of male hours. The top panel displays the volatility of hours, in the aggregate and by gender relative to GDP. Consistent with [18] with

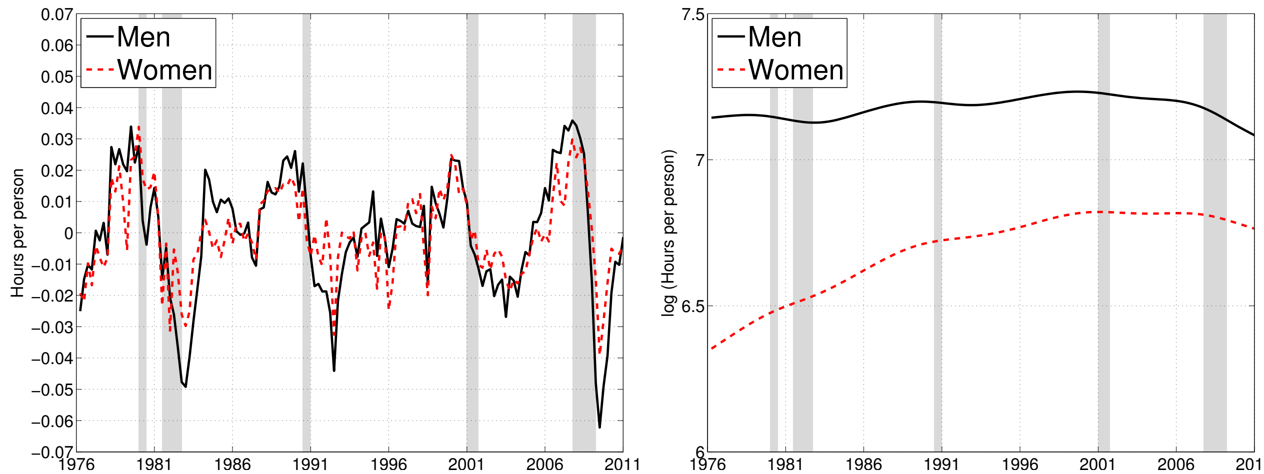


Figure 5: Cyclical component (left) and trend component (right) of quarterly hours by sex. Source: Monthly CPS.

find that the volatility of aggregate per capita hours relative to GDP *rose* in 1985-2005 relative to 1969-1984, from 0.99 to 1.10, and correlation with GDP declined from 0.89 to 0.83. Female hours display lower volatility relative to GDP and a smaller correlation with GDP than male hours in both periods. However, both female and hours exhibit a sizable rise in their standard deviation relative to GDP after 1984 and a modest decline in correlation with GDP. The higher share of female hours tempers the rise in the relative volatility of aggregate hours and strengthens the reduction in the correlation of aggregate hours with GDP.

2.3 Jobless Recoveries

Finally, we consider the emergence of jobless recoveries, that is the slow recovery of employment and hours after a recession, even as output bounces back from its cyclical trough ([23] and [14]). Jobless recoveries first emerged with the 1991 cycle, which corresponds to the flattening in female labor force participation. We show that the flattening of female participation accounts for a large fraction of the jobless recoveries. The strong upward trend in women's labor force participation through the 1970 and 1980s was mirrored in their employment growth and hours per worker, which masked the relatively weak recoveries in the employment and hours of men for cycles in that period. When female participation stopped growing in the early 1990s, the cyclical variation in female hours started to resemble that of men, resulting in very weak growth in aggregate employment and hours in cyclical recoveries.

Figure 6 displays evidence supporting this hypothesis. These charts plot the cumulative changes in the *log* of hours per capita from the unemployment through of the preceding expansion, ending three years after the unemployment peak. As figure 6 shows, in the 1970, 1974-75 and 1981-82 recessions, as women were experiencing a strong positive trend in labor force participation, hours per capita for women drop only slightly if at all during the recession, and experience a strong growth in the recovery. The 1990-91 cycle marks a change in this pattern, as the trend growth in female participation slowed substantially. While the decline in hours for women during the recession is still

Table 1: Business Cycle Volatility Statistics

Cyclicality and Volality of Hours, Aggregate and by Gender

	1969-1984		1985-2005	
	std / std GDP	Corr. With GDP	std / std GDP	Corr. With GDP
GDP	1.00	1.00	1.00	1.00
hours total	0.99	0.89	1.10	0.83
hours men	1.15	0.91	1.41	0.84
hours women	0.76	0.77	0.83	0.61
hours men (fitted)[1]	1.21	0.90	1.30	0.85
hours women (fitted)[1]	0.67	0.81	0.81	0.72

Relative Volatility of female and Male hours

	1969-1984		1985-2005	
	hours	hours (fitted)[1]	hours	hours (fitted)[1]
std female/std male	0.66	0.55	0.59	0.63

Moderation in amplitude of business cycle fluctuations

	GDP	Aggregate Hours (Macro Data)	Aggregate Hours (Micro Data)	Total E/P
Std. Dev. For 1985-2005 over 1969-84	0.47	0.68	0.52	0.56

[1]The fitted hours series are the fitted values of a regression of gender specific hours on GDP and the aggregate version of hours. This specification produces a series for hours with variation coming solely from business cycle movements.

Note: All calculations above are performed on the hp-filtered detrended data using $\lambda = 6.25$.

modest compared to men's, the recovery is weaker than in previous cycles, and also weaker than men's for the 1990-91 cycle. In the 2001 and 2007-09 cycles—when the upward trend in female participation had completely stopped—the behavior of female hours per capita is very similar to men's, except for a more modest amplitude of the fluctuation.[5] Figure 6 also shows that the behavior of male hours was very similar in all these cycles, with the only variation driven by the severity of the recession. Hours per capita always declined for men during recessions and did not regain pre-recession values except for the 1981-82 cycle, with the recovery particularly sluggish in the most recent cycles. These figures show that the changing trend in female participation is reflected in a change in the cyclical behavior for hours for women starting in early 1990s, while for men both the trend and the cyclical behavior of participation has been similar since 1970.

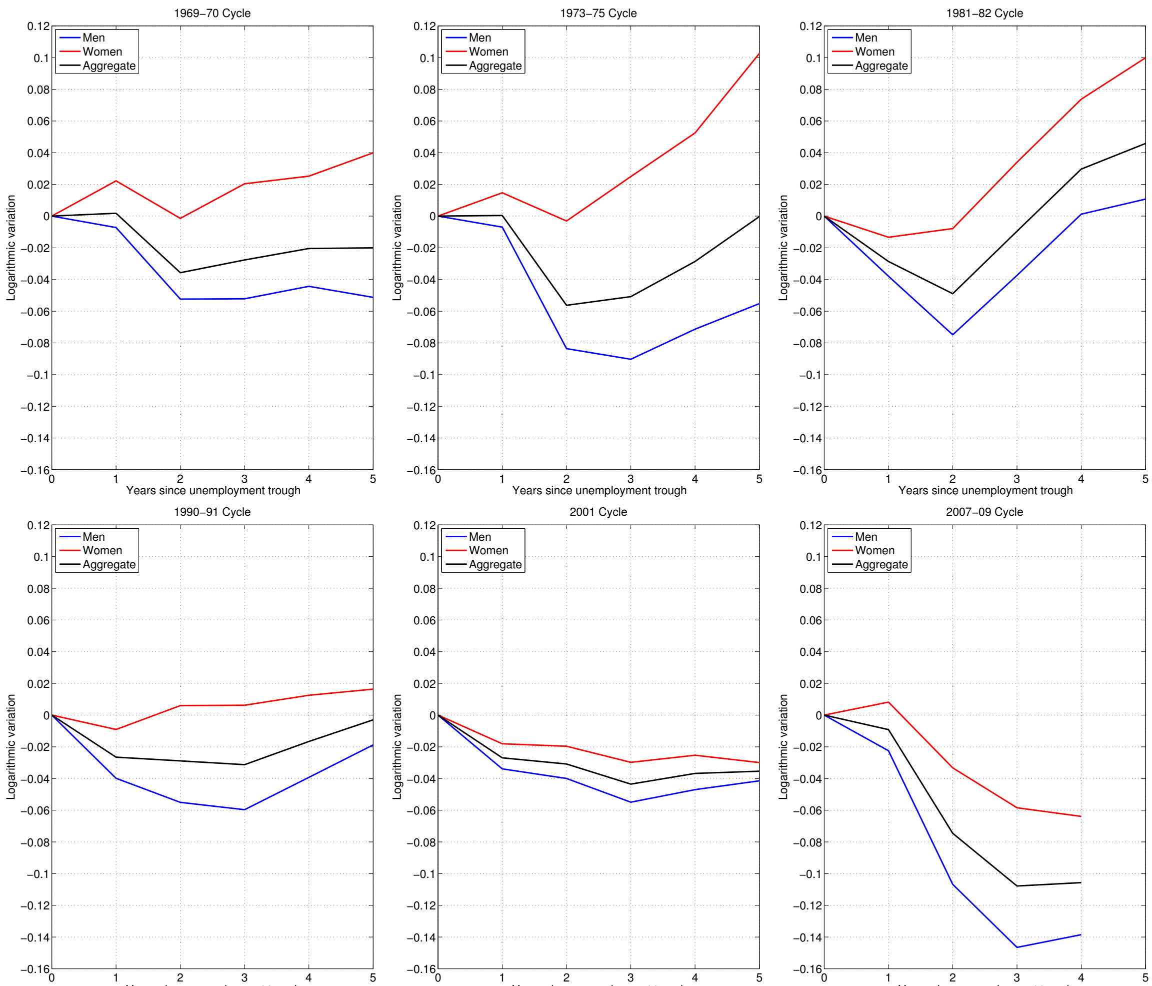


FIGURE 6: Log changes in hours per capita in the aggregate and by gender. Source: Bureau of Labor Statistics.

To quantify the effects of the changing behavior of female hours on aggregate hours we now present some simple counterfactuals. Specifically, we compute counterfactual *aggregate* hours per

[5] [**?**] show that the smaller decline in female hours during the 2007-2009 recession is mostly accounted for by gender differences in the industry distribution.

capita for recent cycles, by replacing the *female* growth rate of hours per capita in each of the last three cycles with the average growth rate of female per capita hours in the early cycles at each date. We keep the evolution of male hours per capita as it is in the data, and compute the counterfactual aggregate using period specific population weights. The results are presented in Figure 7. The scaled counterfactual multiplies the average change in female hours per capita in the early cycles by a factor to match the size of the drop in female per capita hours at the peak of the recession in each of the recent cycles, while the unscaled counterfactual omits this transformation.

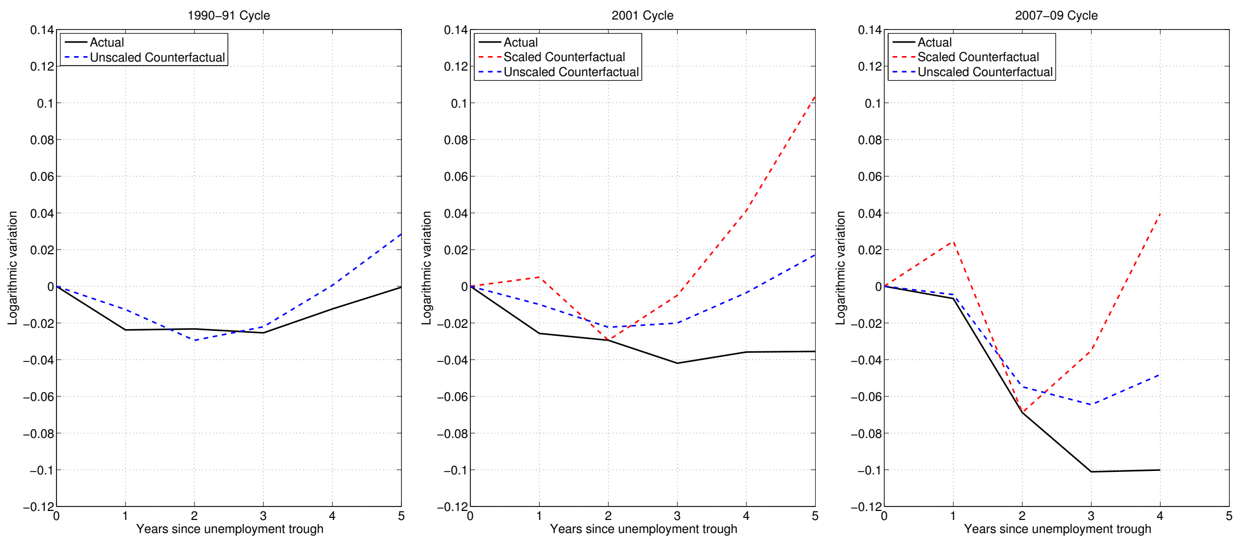


FIGURE 7: Female hours per capita counterfactual: Female hours per capita replaced with average for early recessions.

These counterfactuals reveal that the change in female hours behavior is an important factor in driving aggregate hours during recoveries, especially for the 2001 and 2007-09 cycles. For the 1990-91 cycle, the growth in counterfactual employment is approximately 3 percentage higher than the actual at the end of the cycle.[6] For the 2001 cycle, the unscaled counterfactual is 5 percentage points higher, while the scaled counterfactual is 13 percentage points higher, reflecting the very mild decline in employment during the recession for this cycle. For the 2007-2009 cycle, scaled counterfactual aggregate hours per capita is 4 percentage points above pre-recession levels by the end of the window, and the unscaled counterfactual is 5 percentage points above the actual by the end of the window. Thus, if female hours growth had continued to exhibit the behavior seen for the early cycles, recoveries from the the last three recessions would not have been jobless.

The changes are solely due to the variation in behavior of female hours. The same exercise with male hours shows no difference between actual and counterfactual values of aggregate hours per capita, as seen in figure 8.[7]

[6]The scaled counterfactual cannot be computed for the 1990-91 cycle as female hours per capita rise during the recession for this cycle.

[7]The 2007-09 cycle has the unique feature that hours per capita and other employment indicators continued to decline well after the unemployment rate peaked. This explains the earlier pick up in hours in the counterfactual series for both the female and male counterfactuals, and the smaller cumulative drop in aggregate hours per capita

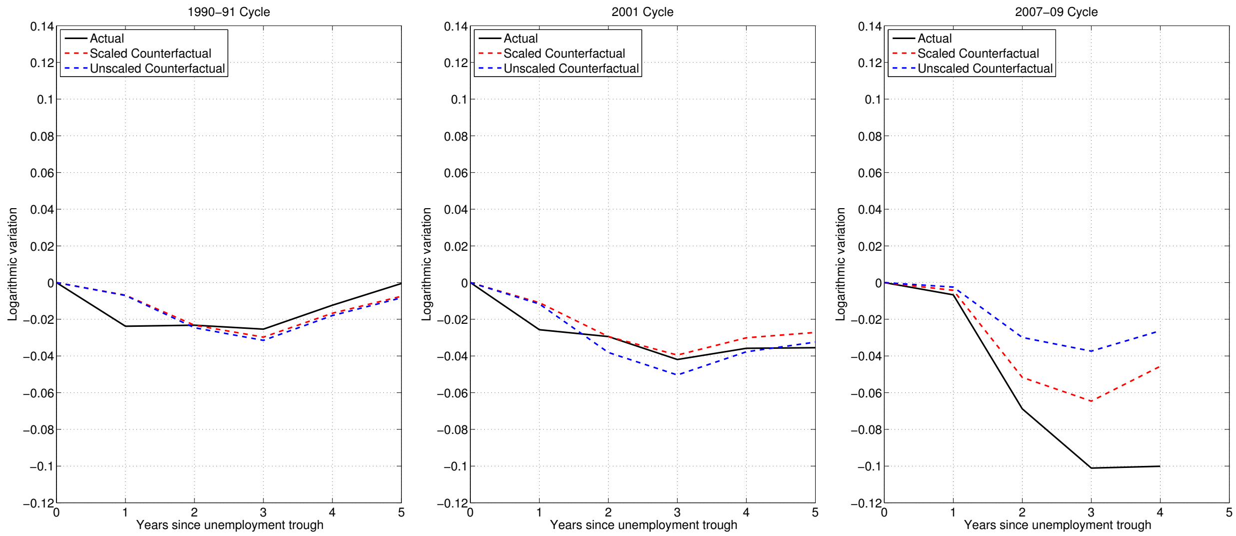


FIGURE 8: Male hours per capita counterfactual: Male hours per capita replaced with average for early recessions.

3 A Real DSGE Model with Gender Differences

For the rest of the analysis, we adapt a real variant of the business cycle model with investment specific productivity shocks and variable capital utilization in [25]. The economy is populated by a representative household and perfectly competitive representative firms. The household is comprised by a continuum of individuals of different gender. Household members have a joint utility from consumption with an internal habit, but exhibit gender specific disutility for supplying labor. The disutility of supplying labor can change over time according to a gender specific persistent shocks. Female and male labor are both used in production, as well as capital. There are time varying gender specific productivity shocks, in addition to an aggregate total factor productivity shock and an investment specific shock.

We now describe each component of the model in detail.

Households The representative household comprises a continuum of unit measure of agents of different gender. A fraction p_t^j of the population is of gender $j = f, m$, where $\sum_{j=f,m} p_t^j = 1$, and all individuals of the same sex are identical. The household utility function is:

$$E_0 \sum_{t=0}^{\infty} \beta^t b_{t+s} \left[log\left(C_t - \eta C_{t-1}\right) - \sum_j p_t^j \varphi_t^j \frac{\left(H_t^j\right)^{1+\nu^j}}{1+\nu^j} \right],$$

for the counterfactual relative to the actual.

where C_t is per capita consumption, η is the degree of habit formation and b_t is a shock to the discount factor, which follows the stochastic process:

$$\log b_t = \rho_b \log b_{t-1} + \varepsilon_{b,t},$$

with $\varepsilon_{b,t} \sim i.i.d.\, N(0, \sigma_b^2)$. H_t^j denotes per capita hours for agents of gender j and φ_t^j is a shock to the disutility of working, which is gender specific. These gender specific utility shocks follow stochastic processes described in section **??**.

This formulation of household utility reflects the assumption that there is consumption sharing within the household, so that all household members consume the same amount and their utility of consumption can be aggregated. The disutility from working, on the other hand, accrues to each member individually, and differs by gender. We allow both the scaling factor for the disutility from labor, $\tilde{\varphi}_t^j$, and the Frisch elasticity $1/\nu^j$ to vary by gender, to match systematic differences in average per capita hours by gender and micro evidence on gender variation in wage elasticity of labor supply

Household members supply labor on competitive markets and the households rent capital. The resulting household budget constraint is:

$$C_t + I_t + T_t \leq \sum_j p_t^j W_t^j H_t^j + r_t^k u_t \bar{K}_{t-1} - a(u_t)\bar{K}_{t-1},$$

where T_t is lump-sum taxes, w_t^j is the real wage for gender j and r_t^k is the rental rate of effective capital. Effective capital is:

$$K_t = u_t \bar{K}_{t-1},$$

where u_t is a utilization rate set by the household, at cost $a(u_t)$ per unit of physical capital $\bar{K}_t$. In steady state, $u = 1$, $a(1) = 0$ and $\chi \equiv \frac{a''(1)}{a'(1)}$. In the log-linear approximation of the model solution this curvature is the only parameter that matters for the dynamics.

The physical capital accumulation equation is:

$$\bar{K}_t = (1-\delta)\bar{K}_{t-1} + \mu_t \left(1 - S\left(\frac{I_t}{I_{t-1}}\right)\right) I_t,$$

where δ is the depreciation rate and the investment shock μ_t follows the stochastic process:

$$\log \mu_t = \rho_\mu \log \mu_{t-1} + \varepsilon_{\mu,t},$$

with $\varepsilon_{\mu,t}$ $i.i.d.N(0, \sigma_\mu^2)$. The function S captures the presence of adjustment costs in investment, as in [10].In steady state, $S = S' = 0$ and $\zeta \equiv S'' > 0$.[8]

[8]Households are assumed to won firms and collect profits, which are zero in equilibrium, and omitted for brevity from the household's budget constraint.

Firms Production is conducted by competitive firms by using capital and labor rented on competitive factor markets. The production function, expressed in per capita terms, is:

$$Y_t = K_t^{\alpha} \left(\tilde{A}_t \tilde{L}_t \right)^{1-\alpha}, \tag{2}$$

where Y_t is output and $\tilde{L}_t$ is a total labor input. Total labor input is derived from hours supplied by male and female workers, and combined according to a CES aggregator:

$$\tilde{L}_t = \left[\omega^f \left(\tilde{L}_t^f \right)^{\rho} + \omega^m \left(\tilde{L}_t^m \right)^{\rho} \right]^{1/\rho}. \tag{3}$$

The parameter $\rho \in (-\infty, 1]$, determines the substitution elasticity between female and male labor inputs, with $\rho = 1$ corresponding to perfect substitutability, $\rho \to -\infty$ corresponding to a Leontieff production function and $\rho \to 0$ representing the Cobb-Douglas case. The parameters $\omega^j \in [0, 1]$ for $j = f, m$, with $\omega^f + \omega^m = 1$, correspond to weight of the gender specific contribution to total labor input. The labor inputs $\tilde{L}_t^j$ are measured in efficiency units per capita:

$$\tilde{L}_t^j = \frac{a_t^j}{a^j} \frac{p_t^j}{p^j} \frac{H_t^j}{H^j}, \tag{4}$$

where a_t^j is a gender specific productivity index. All variables are normalized by their steady state value, which is indicated by dropping the time subscript.

This normalization implies that the steady state value of the effective labor input L_t is normalized to $L = 1$, and the distribution parameters in the CES agregator, ω^j, are equal to the income shares in steady state. To see this, we use the homogeneity of the production structure to normalize the production function as:

$$\begin{aligned} Y_t &= K_t^{\alpha} \left(A_t L_t \right)^{1-\alpha}, \\ L_t &= \left[\omega^f \left(\tilde{a}_t^f \frac{H_t^f}{H^f} \right)^{\rho} + \omega^m \left(\frac{H_t^m}{H^m} \right)^{\rho} \right]^{1/\rho}, \end{aligned}$$

with

$$\begin{aligned} L_t &= \frac{\tilde{L}_t}{\frac{a_t^m}{a^m} \frac{p_t^m}{p^m}}, \\ A_t &= \tilde{A}_t \frac{a_t^m}{a^m} \frac{p_t^m}{p^m}, \\ \tilde{a}_t^f &= \frac{a_t^f / a^f}{a_t^m / a^m} \pi_t^f, \\ \pi_t^f &= \frac{p_t^f / p^f}{p_t^m / p^m}. \end{aligned}$$

Female relative productivity in production then depends on two factors, the ratio of female to male raw productivities, a_t^j/a^j for $j = f, m$, and the relative fraction of women in the population, π_t^f, which in the steady state are both equal to 1, so that relative female productivity in steady state is also equal to 1. It follows that that $L = 1$ and that, if male productivity is stationary, the growth rate of the augmented TFP factor A_t is the same as the growth rate of $\tilde{A}_t$.

The relative efficiency of women follows the stationary stochastic process:

$$\begin{aligned}
\log \tilde{a}_t^f &= \log \tilde{a}_t^{fT} + \log \tilde{a}_t^{fC}, \\
\log \tilde{a}_t^{fT} &= \rho_{a^{fT}} \log \tilde{a}_{t-1}^{fT} + \varepsilon_{a^{fT},t}, \\
\log \tilde{a}_t^{fC} &= \rho_{a^{fC}} \log \tilde{a}_{t-1}^{fC} + \varepsilon_{a^{fC},t},
\end{aligned}$$

with $\varepsilon_{a^{Xf},t}$ i.i.d. $N(0, \sigma^2_{a^{Xf}})$ for $X = T, C$. This decomposition of the relative efficiency into a trend (T) and a cycle (C) component, allows us to isolate the slow-moving component of this process, without at the same time overly restricting its cyclical frequency behavior.[9]

The aggregate technology factor A_t, which compounds total factor and male-specific productivity, follows a stationary AR(1) process in its growth rate $z_t \equiv \Delta \log A_t$:

$$z_t = (1 - \rho_z)\gamma + \rho_z z_{t-1} + \varepsilon_{z,t},$$

with $\varepsilon_{z,t}$ distributed $i.i.d.N(0, \sigma_z^2)$. This specification implies that the level of technology is non stationary.

Resource Constraint The aggregate resource constraint is:

$$C_t + I_t + G_t + a(u_t)\bar{K}_{t-1} = Y_t,$$

where government spending is a time-varying fraction of GDP,

$$G_t = \left(1 - \frac{1}{g_t}\right) Y_t,$$

and the government spending shock g_t follows the stochastic process:

$$\log g_t = (1 - \rho_g)\log g + \rho_g \log g_{t-1} + \varepsilon_{g,t},$$

with $\varepsilon_{g,t} \sim i.i.d.N(0, \sigma_g^2)$.

Equilibrium An equilibrium for this economy can be defined in the standard way. In the following section, we describe the main properties of the equilibrium to provide intuition on the role of gender differences in the model.

[9] A more parsimonious alternative would be to assume that there is no cyclical component in the relative efficiency of the two genders, and that all cyclical fluctuations come from the aggregate component. An intermediate case would be to add to the trend component just an i.i.d. process, rather than an AR(1).

3.1 Solution

Before we proceed to characterize the model solution, we derive some properties of gender ratios in the model that will be useful in deriving the steady state conditions and aid in defining processes for the exogenous gender specific shocks that can identified using data on hours, wages and income shares by gender.

3.1.1 Implications for Wages and Income Shares

The households' and firms' first order necessary conditions for optimality are derived in Appendix A and they imply a number of equilibrium restrictions that are useful for understanding the workings of the model and aspects of the identification in the estimation.

The labor supply equations derived from the household's optimality conditions imply:

$$\frac{W_t^f}{W_t^m} = \frac{\varphi_t^f}{\varphi_t^m} \frac{\left(H_t^f\right)^{\nu^f}}{\left(H_t^m\right)^{\nu^m}}, \tag{5}$$

from which we can recover the *relative* disutility of effort $\tilde{\varphi}_t^f \equiv \frac{\varphi_t^f}{\varphi_t^m}$ from observations on wages and hours worked, given the Frisch elasticities ν^f and ν^m. Specifically, we can write:

$$\log \tilde{\varphi}_t^f = \log W_t^f - \log W_t^m - \nu^f \log H_t^f + \nu^m \log H_t^m. \tag{6}$$

From the mens' labor supply function:

$$W_t^m = \frac{\varphi_t^m \left(H_t^m\right)^{\nu^m}}{\Lambda_t}, \tag{7}$$

where Λ_t is the marginal utility of consumption, it is then possible to recover the level of φ_t^m, conditional on Λ_t.

These equilibrium conditions suggest modelling women's relative disutility and men's absolute disutility of labor as independent processes, as follows:

$$\begin{aligned}
\log\left(\tilde{\varphi}_t^f / \tilde{\varphi}^f\right) &= \log \tilde{\varphi}_t^{fT} + \log \tilde{\varphi}_t^{fC}, \\
\log \tilde{\varphi}_t^{fT} &= \rho_{\tilde{\phi}^{fT}}^T \log \tilde{\varphi}_{t-1}^{fT} + \varepsilon_{\tilde{\varphi}^{fT},t}, \\
\log \tilde{\varphi}_t^{fC} &= \rho_{\tilde{\phi}^{fC}}^C \log \tilde{\varphi}_{t-1}^{fC} + \varepsilon_{\tilde{\varphi}^{fC},t}, \\
\log\left(\varphi_t^m / \varphi^m\right) &= \rho_{\varphi^m} \log \varphi_{t-1}^m + \varepsilon_{\varphi^m,t},
\end{aligned}$$

with $\varepsilon_{\tilde{\varphi}^{fX},t}$ is i.i.d. as $N(0, \sigma_{\tilde{\varphi}^{fX}}^2)$ for $X = T, C$ and $\varepsilon_{\varphi^m,t}$ is i.i.d. as $N(0, \sigma_{\varphi^m}^2)$.The averages of the φ processes pin down the levels of hours for men and women in steady state, but have no effect on the model's dynamics. We do not exploit this restriction, since the hours used in estimation are in deviation from their steady state value.

This parametrization parallels the one adopted for the gender specific productivities, and similar considerations hold in terms of the trend/cycle decomposition.[10]

The labor demand equations derived from the firms' optimality conditions determine the labor income shares by gender:

$$\frac{W_t^f H_t^f}{Y_t} = (1-\alpha)\,\omega^f \left(\frac{\tilde{a}_t^f \left(H_t^f / H^f \right)}{L_t} \right)^{\rho}, \tag{8}$$

$$\frac{W_t^m H_t^m}{Y_t} = (1-\alpha)\,\omega^m \left(\frac{\left(H_t^m / H^m \right)}{L_t} \right)^{\rho}, \tag{9}$$

and relative labor incomes:

$$\frac{W_t^f H_t^f}{W_t^m H_t^m} = \frac{\omega^f}{\omega^m} \left(\tilde{a}_t^f \frac{H_t^f}{H_t^m} \right)^{\rho}. \tag{10}$$

These equations imply that the *relative* paths for gender specific productivity can be easily recovered from observations on hours and wages, given the CES parameter ρ:

$$\log \tilde{a}_t^f = \frac{1}{\rho} \left[\log W_t^f - \log W_t^m - \log \frac{\omega^f}{\omega^m} \right] + \left(\frac{1}{\rho} - 1 \right) \left[\log H_t^f - \log H_t^m \right]. \tag{11}$$

Unitary household utility from consumption and the separability of utility between consumption and labor imply that the marginal utility of income is equalized across genders. It follows that:

$$\frac{\left(H_t^m\right)^{\nu^m}}{W_t^m} = \frac{\tilde{\varphi}_t^f \left(H_t^f \right)^{\nu^f}}{W_t^f},$$

which combined with the firm's optimality conditions implies:

$$\frac{\left(H_t^m\right)^{1+\nu^m-\rho}}{\frac{\omega^m}{(H^m)^{\rho}}} = \frac{\tilde{\varphi}_t^f \left(H_t^f \right)^{1+\nu^f-\rho}}{\frac{\omega^f}{(H^f)^{\rho}} \left(\tilde{a}_t^f \right)^{\rho}}. \tag{12}$$

This equation clearly shows that both the efficiency and the disutility factor have an effect on hours in equilibrium. This would not be the case under a Cobb-Douglas specification, in which $\rho = 0$, since with that specification income and substitution effects of the increase in gender-specific productivity and wages cancel out.

[10] One difference is that, unlike for the productivities, whose level is not separately identified from that of the share parameters ω^j, the steady state levels of the disutility of work φ could be identified from information on the level of hours and wages by gender. However, we only retain information on the relative levels of hours and wages to pin down the relative disutility in steady state $\tilde{\varphi}^f$.

3.1.2 Steady State

Total factor productivity A_t is not stationary in the model, therefore, we define normalized stationary variables that are constant relative to GDP in a non-stochastic version of the model, and then characterize the solution of the model in terms of these rescaled variables. This economy also features two additional variables that could potentially be non-stationary. These are female disutility from work shock $\tilde{\varphi}_t^f$ and the female relative productivity $\tilde{a}_t^f$. As shown in figure 9, female hours and the female income share are stable relative to male hours and income shares in 1995-2005. In the estimation, we will treat this period as the steady state, as all variables, either rescaled or in levels, are stable over this time period. Consistent with this empirical behavior, we posit that $\overline{\tilde{\varphi}^f}$ and $\tilde{a}_t^f$ are constant in the steady state.

The derivation of the aggregate variables in steady state is standard and is presented in Appendix A.3. In addition, equations 8 and 9 pin down the female and male labor share in the steady state:

$$
\begin{aligned}
w^f &= (1-\alpha)\,\frac{y}{H^f}\omega^f, \\
w^m &= (1-\alpha)\,\frac{y}{H^m}\omega^m,
\end{aligned}
$$

for $j = f, m$. which are equal to ω^f and ω^m, respectively. Additional details of the steady state derivation can be found in Appendix A.3.

3.1.3 Dynamics

The full equilibrium characterization, the log linearization and the derivation of the state equations are presented in detail in Appendix A. Here, we focus on some key dynamic properties of the model that are useful in understanding the role of the changing trends in female hours and wages for aggregate outcomes. Specifically, the differentiation by gender of hours and productivity provide a theory for the Solow residual and aggregate labor productivity, and drive a set of low frequency correlations between these variables and aggregate per capita hours that are different from those that would arise in standard RBC model.

Solow residual and aggregate labor productivity The log variation of output around the steady state is:

$$\hat{y}_t = (1-\alpha)\hat{z}_t + \alpha\hat{k}_t + (1-\alpha)\hat{L}_t, \tag{13}$$

where k_t denotes effective capital and includes utilization and the last term corresponds to the log variation from steady state of the labor supply aggregator:

$$\hat{L}_t = \left[\omega^f\left(\hat{\tilde{a}}_t^f + \hat{h}_t^f\right) + \omega^m \hat{H}_t^m\right]. \tag{14}$$

We can express aggregate hours per capita as:

$$H_t = \pi_t^f \frac{H_t^f}{H^f} + \frac{H_t^m}{H^m}. \tag{15}$$

Here, we use actual hours, not hours in efficiency units, as these correspond to measured hours in the data and would be the relevant concept of hours for deriving the Solow residual and aggregate labor productivity. Moreover, this definition of aggregate hours per capita implies that their state stave value H is equal to 1, consistent with the scaling adopted for the labor input aggregator in equation 3. Then, the log variation in aggregate per capita hours from the steady state is:

$$\hat{H}_t = \hat{h}_t^f + \hat{\pi}_t^f + \hat{H}_t^m. \tag{16}$$

The ratio of total labor input to aggregate per capita hours is 1 in the steady state, but different from 1 outside the steady state. To see this note that:

$$\frac{L_t}{H_t} = \frac{\left[\omega^f \left(\tilde{a}_t^f h_t^f\right)^\rho + \omega^m\right]^{1/\rho}}{\left(\pi_t^f h_t^f + 1\right)},$$

where $h_t^f = \frac{\frac{H_t^f}{H^f}}{\frac{H_t^m}{H^m}}$ denotes the female/male hours ratio, which in steady state is equal to 1. Since $\tilde{a}_t^f = \pi_t^f \frac{a_t^f/a^f}{a_t^m/a^m}$, $\tilde{a}_t^f < \pi_t^f$ outside of the steady state. Moreover, $h_t^f < 1$ outside of the steady state, which since $\rho \in (0, 1]$ implies that $\left(\tilde{a}_t^f h_t^f\right)^\rho < \pi_t h_t^f$.

Based on the production function in (2), (14) and (16), the log variation of the Solow residual around the steady state, denoted with $\hat{s}_t$ can be written as:

$$\hat{s}_t = (1-\alpha)\hat{z}_t + \alpha\hat{u}_t + (1-\alpha)\left(\omega^f \hat{\tilde{a}}_t^f - \hat{\pi}_t^f\right). \tag{17}$$

Then, if female relative productivity is growing faster than the female population share, that is $\omega^f \hat{\tilde{a}}_t^f > \hat{\pi}_t^f$, the growth in female relative productivity contributes positively in variations of the Solow residual.

We can derive a similar expression for the log variation from steady state of aggregate labor productivity, which we will denote with P_t:

$$\hat{P}_t = (1-\alpha)\hat{z}_t + \alpha\left(\hat{u}_t + \hat{\overline{k}}_t\right) - \alpha\left(\hat{H}_t^m + \hat{\pi}_t^f\right) + \left[(1-\alpha)\omega^f - 1\right]\hat{h}_f^f + (1-\alpha)\left(\omega^f \hat{\tilde{a}}_t^f - \hat{\pi}_t^f\right), \tag{18}$$

where $\overline{k}_t$ is measured capital. As usual, growth in female or male aggregate per capita hours contributes negatively to the growth in average labor productivity, since $(1-\alpha)\omega^f < 1$. The growth in female relative productivity contributes positively to the growth in female relative productivity only if the labor share is large enough and female relative productivity grows faster than the female share in the population, as for the Solow residual. Moreover, for a large labor share (low α), it is more likely that a positive growth in relative female hours and relative productivity will jointly on net contribute positively to average labor productivity growth.

Correlation between output, productivity and hours It is clear from these expressions that the the correlation between productivity, output and aggregate hours depends on the medium run fluctuations in female relative productivity and hours. [18] isolate three important facts about the Great Moderation and the behavior of output, productivity and hours.

- The volatility of aggregate per capita hours and labor productivity fell in 1984-2005, and the timing in the decline varies. Specifically, the decline in the absolute volatility of output and hours started in 1978, while the decline in the volatility of productivity started in 1974 and stopped in the late 1980s.

- There was a sizable decline in the correlation between hours and productivity from zero to negative, starting with the decline in output volatility. Over the same period, the correlation between output and labor productivity decline from positive to zero.

- There were large medium run swings in the correlation between these three variables. The correlation of output and hours to productivity experienced a sharp decline starting in the 1980s, accelerating in the 1990s. The correlation of hours to productivity and output *conditional* on technology shocks rises in the late 1970s and mid-1990s.

Based on equation (18), for given $\hat{z}_t$, $\hat{u}_t$, $\hat{k}_t$, $\hat{H}_t^m$, faster growth in female relative hours and productivity increases the growth in output and in aggregate hours per capita, generating a positive correlation between these variables. However, if the growth rate in female relative hours is too fast relative to the growth in female relative productivity, that is $\left[(1-\alpha)\omega^f - 1\right] \hat{h}_f^f + (1-\alpha)\left(\omega^f \hat{\tilde{a}}_t^f - \hat{\pi}_t^f\right) < 0$, there will be a negative correlation between output, hours and average labor productivity.

The path of the female/male income share depends on both the female/male wage ratio and the female/male hours ratio, as shown in equation (10). We can use equation (11) to compute the path of $\tilde{a}_t^f$ from female relative hours and income shares, using the calibrated values of ρ and ω^f discussed in Section 4. Figure 9 presents the female/male ratios of hours and income shares between 1969 and 2011, key variables in identifying the female labor supply and relative productivity shocks.

There are clear breaks in the growth rate of the female/male hours ratio in 1974, 1983, 1993 and 2005, and in 1974, 1993 and 2005 for the female/male income share. Figure 10 reports the average yearly log variation of the female labor surprise and relative productivity shocks, and the contribution of the growth in female hours and productivity to the Solow residual and aggregate labor productivity for selected sub periods corresponding to these breaks. The female labor supply shock and female relative productivity are calculated from the historical path of the female/male hours and income ratios computed using equation 11, with the calibrated value of ν^f, ν^m, and ρ, derived in Section 4.

The contribution of the growth in female hours to the Solow residual is mostly positive but small throughout the sample period, while the contribution to average labor productivity is negative and

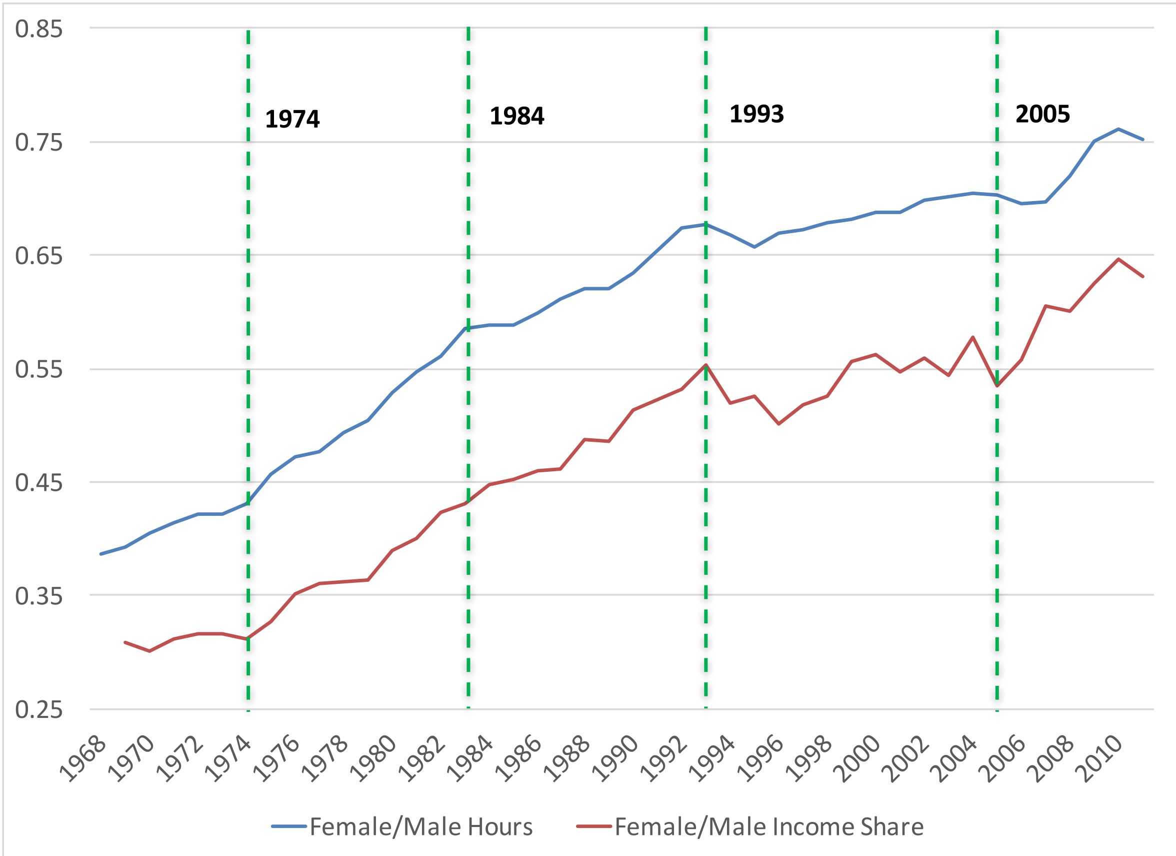


FIGURE 9: $\frac{H_t^f}{H_t^m}$ and female/male labor share ratios. Source: Current Population Survey.

sizable in most sub periods. The period from 1974 to 1983 exhibits the highest decline in the female labor supply shock and also a decline in the female relative productivity shock. The latter is mostly driven by selection, as younger women with lower education and less experience enter the workforce. This pattern leads to a large negative contribution of the female shocks to average labor productivity. Aggregate per capita hours exhibit high average yearly growth rate in this period, which is consistent with a negative correlation between the log variation in aggregate per capita hours and average labor productivity. Starting in 1984, changes in the female labor supply shocks are muted, while the female relative productivity shock grows strongly in 1984-1993 and 2005-2011. Since female hours continue to grow in 1984-1993, this suggests that the rise in female relative wages is driving the increase in female labor supply in these years. This is period in which the female contribution to the Solow residual is higher, and the negative contribution to average labor productivity smaller than in the previous period, even though aggregate per capita hours still exhibit a strong average yearly growth rate. This is consistent with a negative but lower in absolute value correlation between productivity and aggregate hours. The 1994-2005 period stands out, since there are no major changes in the female shocks or their contribution to the Solow residual or aggregate labor productivity. Aggregate hours grow very modestly, while average labor

FIGURE 10: Average yearly log variation by subperiod. Source: Current Population Survey.

productivity and GDP per capita show strong growth. The 2006-2001 year are dominated by the Great Recession and display a very large decline in aggregate per capita hours and GDP per capita and a sizable growth in average labor productivity. Female relative productivity records the highest average yearly growth over this period, likely due to the fact women in the labor force pass men in educational attainment in these years.As a consequence, the female contribution to the Solow residual is strongest in this period, even as the female contribution to average labor productivity remains negative.

4 Estimation

Our estimation procedure is guided by the behavior of the female/male hours ratio and of the income shares by gender, since these variables are critical to identify the gender specific parameters and shocks. As shown in figure 10, the growth of female hours relative to men's is strongest between 1974 and 1983, slows down slightly in 1984-1993 and is very close to zero between 1994 and 2004. The female/male income share grows at the same rate as the female/male hours ratio on average between 1974 and 1993, and then flattens out between 1994 and 2004. Thus, we take the 1995-2004 decade to correspond to the steady state in the model, as female hours and the female income share are stable relative to male hours and the male income share over that period. After 2004 we see an increase in female relative hours and wages, mainly driven by the 2007-2009 recession, in which male job loss exceeded women's.[11]

The state equations for the 13 endogenous variables are derived in Appendix A.4. The process for the exogenous shocks used in the estimation is reported in Appendix A.5 and the resulting version of the corresponding state equations is presented in Table 4. We use the steady state equations described in Section to calibrate certain parameters of the model for which independent evidence is available, and we estimate all remaining structural parameters using Bayesian methods (see for example [5]). We describe the calibration strategy and the structural parameters below.

Calibrated Parameters We assume that the steady state of the normalized model corresponds to the time period 1995-2005, when female hours relative to male hours and female income share relative to male income share are stable and choose parameters accordingly. Standard estimates (e.g. [8]) suggest that women's Frisch elasticity of labor supply is approximately three times as large as men's. Assuming a typical macro elasticity of 2.84 (see for example [9]), and given women's share in total hours of 0.4 for 1995-2005, we have:

$$0.4\frac{3}{\nu^m} + 0.6\frac{1}{\nu^m} = 2.84$$

or $1/\nu^m = 1.58$ and $1/\nu^f = 4.73$.

The substitution elasticity between female and male labor is $1/(1-\rho)$. Plausible estimates based on [1] range between 3.2 and 4.2. We take 4 as a benchmark, which implies $\rho = 0.75$. The observed average relative labor share of women over the period 1995 to 2011 is 0.60. This implies $\frac{\omega^f}{\omega^m} = 0.60$ and $\omega^f + \omega^m = 1$, which imply $\omega^m = 0.625$ and $\omega^f = 0.375$.

Finally, the steady state share of government spending in GDP $(1 - 1/g)$ is calibrated to 0.15, which roughly corresponds to the average share of G+NX in GDP over the period 1995 to 2005. Table 1 summarizes the calibrated parameters.

Estimated Parameters The structural model parameters that are estimated include γ, the trend growth rate in aggregate technology, ξ, the curvature of the capital utilization cost at full utilization, η, the habit parameter, and ζ, the second derivative of the investment adjustment cost in a non-stochastic steady state. They are summarized in Table 2.

The priors for all the aggregate shocks follow [26]. For the persistence of the trend components of the labor supply shocks preferences and the female relative productivity factor, that is $\rho_{\tilde{\varphi}^{fT}}$ and

[11]See [4] for a discussion.

TABLE 1: Calibrated parameters.

Parameter	Description	Value
α	capital share	0.33
β	discount factor	0.99
δ	depreciation rate	0.025
g	output share of government spending	$\frac{1}{1-0.15}$
ν^f	inverse Frisch elasticity, female	0.21
ν^m	inverse Frisch elasticity, male	0.63
ρ	substitutability of female&male hours in labor input	0.75
ω^f	steady state labor share, female	0.375
ω^m	steady state labor share, male	0.625

TABLE 2: Estimated parameters.

Parameter	Description
γ	TFP growth rate
ξ	curvature of capital utilization cost
η	consumption habit parameter
ζ	curvature of investment adjustment cost
ρ_x	autocorrelation coefficient for shock x
σ_x	standard deviation for the error term for shock x
Shocks	z, μ, b, g, $\tilde{a}^{fT}$, $\tilde{a}^{fC}$, $\tilde{\phi}^{fT}$, $\tilde{\phi}^{fC}$, ϕ^m

$\rho_{\tilde{a}^{fT}}$, we center the prior tightly around 0.98, given the observed persistence of the female/male hours and wage ratios. For the cyclical components, we center the prior on the autocorrelation around 0.4, which is the same as for the growth rate of the technology shock, reflecting the view that the persistence of the cyclical component should be significantly smaller than that of the trend.

Observation Equations We use log GDP growth, log consumption growth, log investment growth, log male hours, log of the female/male hours ratio and the log of the male income share as observables. Since we are not interested in average levels of variables over the entire sample, we will compute the observables in deviation from their steady state value and omit the constant in the observation equations.[12] The observation equation are presented in Table 5 in Appendix A.

Strategy Since we are interested in assessing the impact of the changing trends in female hours and wages on aggregate outcomes, we run the estimation over different sample periods, corresponding to the evolution of the growth in relative female hours and wages. We use annual data for 1969-2011, since this allows us to go back further in time.

For comparison, we also estimate a real version of the model in [26], which is identical to our

[12]In most DSGE applications, it would be of interest to estimate the steady state level of hours for the entire sample period. The system of equations characterizing the steady state could be used for this purpose, as discussed in Section **??**, so that the 1995-2005 level of a value for the φ^j and a^j would be pinned down from the steady state equations using the level of hours and wages.

model, except for the fact that there are no gender specific shocks and no differentiation between male and female hours, so that the disutility of labor and the production function are defined over aggregate hours per capita. We consider two versions of this model. The first has an aggregate labor supply shock that scales the disutility of hours in the household utility function, similar to the female labor supply shock in the full model. The second version reduces this shock to a fixed parameter, which is estimated. The priors for the aggregate shocks for both versions of the simple model are set the same as for the full model, and the prior for the aggregate labor supply shock in the first version of the simple model is set the same as the prior for $\tilde{\phi}^{fT}$ in the full model. We will refer to the model without gender differentiation as the *simple* model, and to our model with gender differences as *full* model when presenting our results.

4.1 Full Model

Table 3 presents the parameter estimates for the period 1969-2011. The gender specific shocks display high degrees of autocorrelation, whereas the aggregate shocks display much lower estimated autocorrelation parameters compared to estimates in the literature. The mode of the estimated autocorrelation of the trend component for the female labor supply and relative productivity shocks are both equal to 0.99. The modal estimate for the same parameter for the male labor supply is shock is 0.92, whereas the model estimate for the autocorrelation coefficient for the technology shock is 0.25. The modal estimates of the standard deviation of the cyclical components of the gender specific shocks are about 1/2 of the magnitude than those of the technology shock.

4.1.1 Estimated Gender Specific Shocks

It is interesting to examine the estimated path of the gender specific processes introduced in the model, $\tilde{a}_t^{fT}$, $\tilde{\phi}_t^{fT}$ and ϕ_t^m, displayed in figure 11. There is a clear and precisely estimated trend for all these processes until the mid-1980s. The path of $\tilde{a}^{fT}$ decreases slightly between 1969 and 1974, and increases very rapidly between 1974 and 1997, with a faster rate between 1984 and 1993. After a drop in the mid 1990s, it continues to grow at a slower rate. The initial decline in relative female productivity is consistent with a decline in the quality of women in the labor force as female participation increased.The following rise reflects the growth in educational attainment of women in the labor force relative to men. The slower rate of growth of female relative productivity in the 1990s is consistent with the sharp rise in the skill premium for men, while it remained constant for women, and a decline in the participation of high skill women over this period, as documented in [3]. By contrast, $\tilde{\phi}^{fT}$ is flat between 1969 and 1974 and then declines at a steady rate until 1994, flattens until 2005, reflecting the path of female labor force participation over this period, and rises thereafter. The male labor supply shock, ϕ^m, also declines between the early 1980s and the mid 1990s, flattens in the early 2000s and then rises after 2006, consistent with the decline in male employment over that period. The initial decline in ϕ^m is modest compared to ϕ^{fT}, and can be attributed to demographics as baby boomers enter the labor force in the 1970s. Figure 12 presents the estimated path of the cyclical components of the gender specific shocks. Both series

Table 3: Estimated Parameters, 1969-2011.

	Prior					Posterior				
	Dist	10%	Median	90%		Mode	Mean	SE	10%	Median	90%
γ	N	3.0000	0.4616	0.5000	0.5384	0.5000	0.5000	0.0306	0.4633	0.5014	0.5429
χ	G	2.0000	3.7689	4.9335	6.3167	5.4282	5.4282	1.0583	4.3050	5.6099	7.0777
η	B	1.0000	0.3701	0.5000	0.6299	0.4384	0.4384	0.0766	0.3286	0.4216	0.5252
ζ	G	2.0000	1.5236	2.5776	4.0345	2.1287	2.1287	0.6843	1.7232	2.4049	3.4789
ρ_b	B	1.0000	0.3205	0.6143	0.8574	0.0740	0.0740	0.0653	0.0399	0.1001	0.2075
ρ_μ	B	1.0000	0.3205	0.6143	0.8574	0.3022	0.3022	0.1241	0.1679	0.3225	0.4892
ρ_z	B	1.0000	0.1426	0.3857	0.6795	0.2531	0.2531	0.1489	0.1015	0.2751	0.4902
ρ_g	B	1.0000	0.3205	0.6143	0.8574	0.8181	0.8181	0.1105	0.6406	0.8237	0.9236
$\rho_{\tilde{a}f,T}$	B	1.0000	0.9599	0.9836	0.9954	0.9880	0.9880	0.0132	0.9608	0.9813	0.9933
$\rho_{\tilde{a}f,C}$	B	1.0000	0.2306	0.5000	0.7694	0.6961	0.6961	0.1637	0.4234	0.6646	0.8546
$\rho_{\phi f,T}$	B	1.0000	0.9599	0.9836	0.9954	0.9908	0.9908	0.0124	0.9644	0.9851	0.9949
$\rho_{\phi f,C}$	B	1.0000	0.2306	0.5000	0.7694	0.6454	0.6454	0.1836	0.3294	0.5985	0.8194
$\rho_{\phi m}$	B	1.0000	0.3205	0.6143	0.8574	0.9320	0.9320	0.0745	0.7719	0.8926	0.9554
σ_b	IG1	4.0000	0.0260	0.0600	0.1880	0.0160	0.0160	0.0024	0.0139	0.0166	0.0202
σ_μ	IG1	4.0000	0.1470	0.3250	0.9390	0.1736	0.1736	0.0582	0.1433	0.1949	0.2803
σ_z	IG1	4.0000	0.3760	0.7480	0.9990	0.1612	0.1612	0.0125	0.1594	0.1710	0.1904
σ_g	IG1	4.0000	0.1470	0.3250	0.9390	0.0687	0.0687	0.0060	0.0664	0.0724	0.0820
$\sigma_{\tilde{a}f,T}$	IG1	4.0000	0.0530	0.1220	0.3760	0.0466	0.0466	0.0075	0.0388	0.0476	0.0580
$\sigma_{\tilde{a}f,C}$	IG1	4.0000	0.1130	0.2530	0.7520	0.0704	0.0704	0.0091	0.0621	0.0719	0.0849
$\sigma_{\phi f,T}$	IG1	4.0000	0.0530	0.1220	0.3760	0.0496	0.0496	0.0093	0.0424	0.0522	0.0654
$\sigma_{\phi f,C}$	IG1	4.0000	0.1130	0.2530	0.7520	0.0736	0.0736	0.0115	0.0645	0.0765	0.0943
$\sigma_{\phi m}$	IG1	4.0000	0.1470	0.3250	0.9390	0.0902	0.0902	0.0123	0.0801	0.0942	0.1122

Annual data. Posterior log density at mode: 344.3191.
Source: Author's calculations from CPS and BLS data.

display lower high frequency volatility and higher medium frequency volatility of female relative productivity cyclical shock starting in mid 1980s, when the corresponding trend component slows.

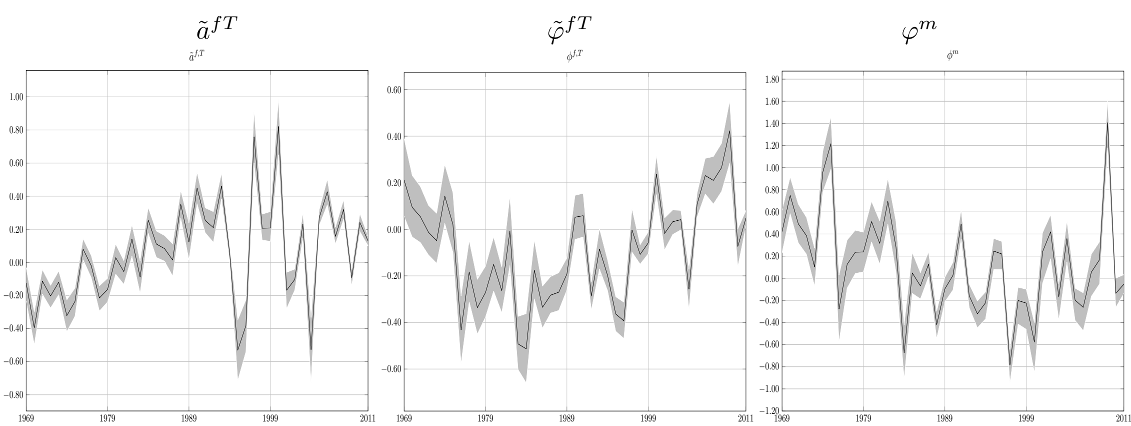


Figure 11: Estimated Paths of Gender Specific Shocks $\tilde{a}^{fT}$ (left), $\tilde{\phi}^{fT}$ (center) and ϕ^m (right). Annual data, 1969 to 2011.

We will discuss the behavior of the estimated aggregate shocks in Section 4.2.

4.1.2 Variance Decomposition

The gender specific shocks account for a sizable fraction of the variance of female and male hours, and female wages, as displayed in figure 13. By year 5, $\tilde{\phi}^{fT}$ alone explains more than 50% of the

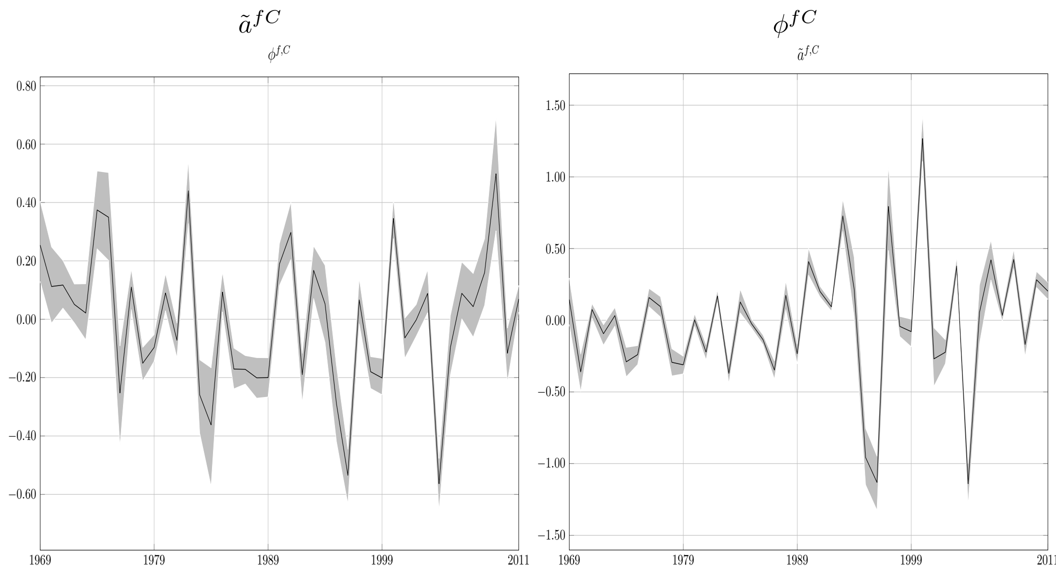


FIGURE 12: Estimated Paths of Gender Specific Shocks $\tilde{a}^{fC}$ (left), $\tilde{\phi}^{fC}$(right). Annual data, 1969-2011.

variation in female hours, while $\tilde{\phi}^{fC}$ explains from 25-10% of the variation at horizons 1-5 years. The trend component of the female labor supply shock explains more of the variation in female hours at horizon 2-4 years than the cyclical component, suggesting that the trend component also influences the cyclical behavior of female hours. The trend component of the female relative productivity shocks explains 10-15% of the variance of female hours at horizons greater than 5 years, while the contribution of the cyclical component of this shock reaches at most 5% at a 1-2 year horizon. The male labor supply shock explains 35-55% of the variance of male hours, depending on the horizon. The female labor supply and productivity shocks account jointly for 15-20% of the variation in male hours.

The productivity shock accounts for for over 70% of the variation of female wages and over 90% of the variation of male wages at horizons greater than 3 years. For female wages, the trend component of the female relative productivity shock explains 12-15% of their variance, while the trend component of the female labor supply shock explains about 10%, both at horizons greater than 4 years. The cyclical components of both the female productivity shock and the labor supply shock jointly account for 40-10% of the variance of female wages at horizons smaller than 4 years. For male hours, the male labor supply shock explains 15-8% of the variation in male wages at horizons smaller than 4 years, while its contribution becomes negligible at longer horizons. Interestingly, while the contribution of the male labor supply shock to male hours and wages declines with horizon, the opposite is true for the contribution of the female productivity and labor supply shocks.

The gender specific shocks are introduced to account for the heterogeneity across genders in the trend in wages and hours. They also matter for aggregate variables. This can be clearly seen from the variance decomposition of aggregate variables. The results are displayed in figure 14, where the horizontal axis denotes the horizon in years. The gender specific shocks account for a sizable fraction of the variance of output, the labor aggregator and investment at horizons greater than

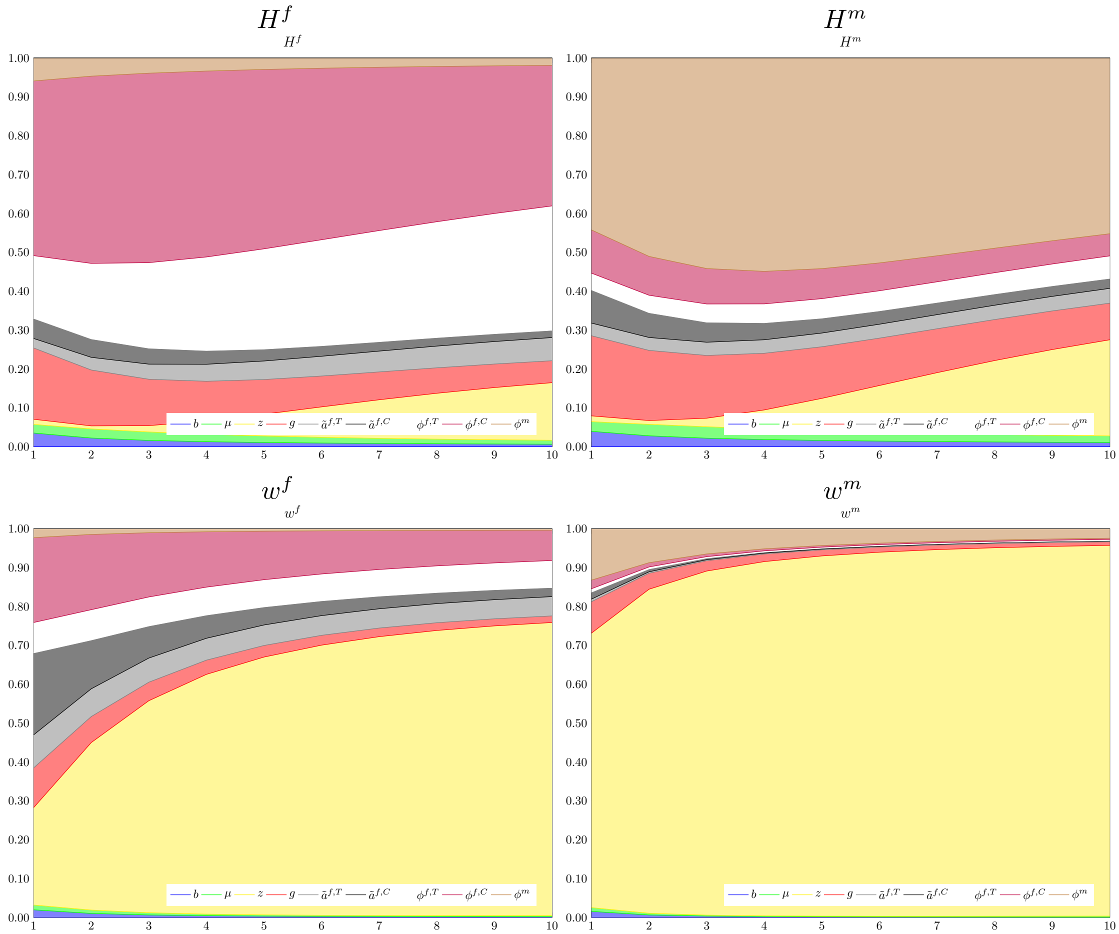


FIGURE 13: Variance Decomposition. H^f (top right), w^f top left, H^m (bottom left), w^m (bottom right). Annual data, 1969-2011.

5 years. Specifically, $\tilde{a}^{fT}$, $\tilde{\phi}^{fT}$ each account for approximately 10-20% of the variance of output and aggregate per capita hours, and jointly approximately 10% of the variance of investment at a 5-10 year horizon. For $\tilde{\phi}^m$, the fraction of the variance accounted of output, the aggregate labor input and investment are somewhat smaller, between 5-10%, the shock having a larger impact on these variables at a 2-5 year horizon. At horizons greater than 5 years, the three gender specific shocks combined explain more of the variance of output that the technology shock, and a similar fraction of the variance of the aggregate labor input as the technology shocks. Interestingly, at horizons greater than 5 years, the three gender specific shock explain about twice the fraction of the variability of investment accounted for by the investment shock and the government consumption shock combined. The variance of consumption is mostly accounted for by the technology shock at all horizons.

4.2 Comparison with Simple Model

We now compare the results for the estimated parameters, aggregate states and variance decompositions with the simple model. We consider two variants of this model. One with a labor supply

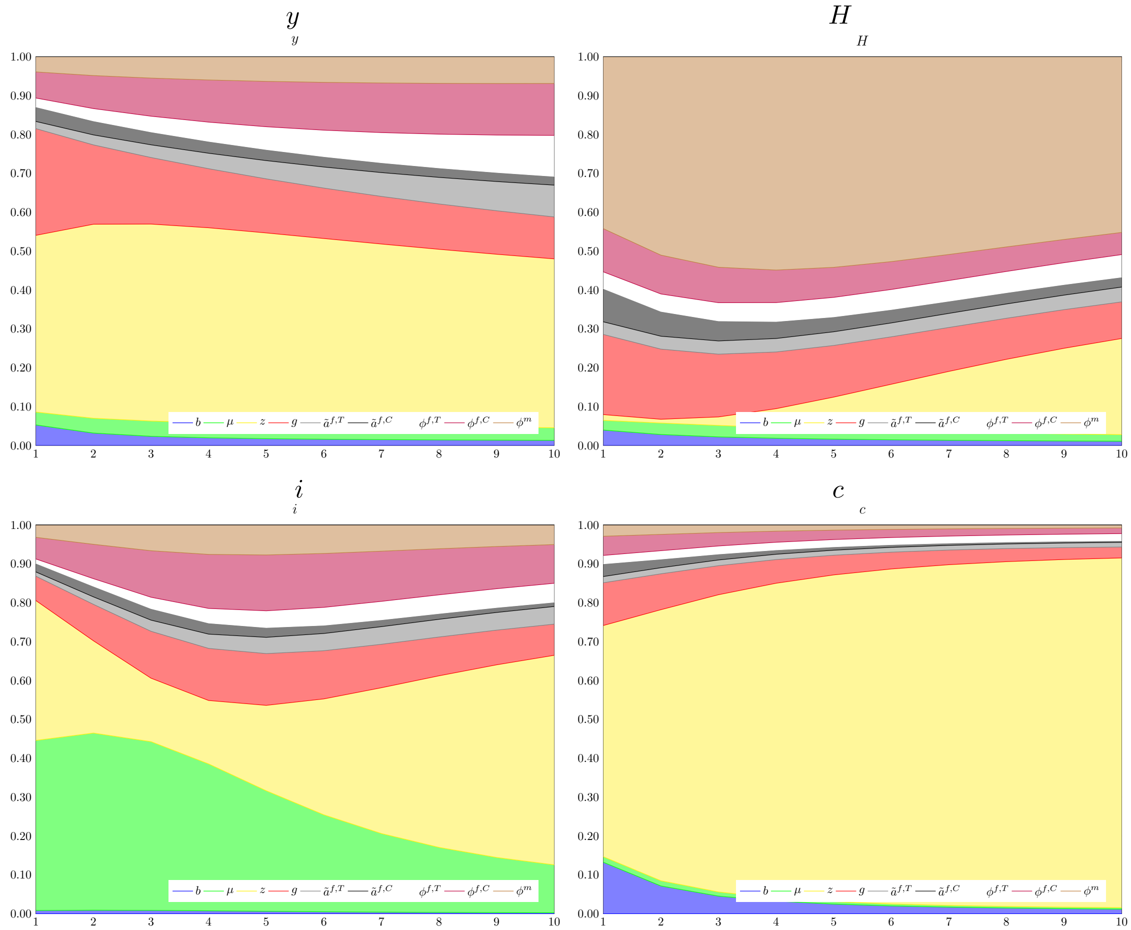


FIGURE 14: Variance Decomposition, Full Model. Output (top left), aggregate labor input (top right), investment (bottom left), consumption (bottom right). Annual data, 1969-2011.

shock, denoted with $\varphi_t = \varphi_t^T + \varphi_t^C$, with a trend and a cyclical component, similar to the female shock in the full model. We also consider a version of the model in which this shock is reduced to a fixed parameter ϕ, that scales the disutility of hours and is estimated. The calibrated parameters that are common to the full and simple models are set to the same values. The curvature of the disutility of labor, which we denote with ν in the simple model is set to $1/2.84$, following the same calibration strategy adopted for the full model. All the aggregate shocks have the same specification as in the full model and the estimation starts from the same priors for all the common parameters.

We start by comparing estimated parameters, which are reported in Appendix C for both versions of the simple model. Table 8 presents the estimates for the version with the labor supply shock. The maximized log-likelihood about 2/3 of full model, and as in the full model, both the trend and cyclical component of the labor supply shock are very persistent, which reduces the estimated autocorrelation of the other aggregate shocks relative to estimates found in the literature, such as [26]. Table 9 presents the estimates for the version with constant ϕ. The maximized log-likelihood is similar to the simple model with the labor supply shock, however, several important parameters display sizable differences in their estimated values. Specifically, the absence of a labor supply shock substantially increases the estimated autocorrelation of the demand shocks. The autocorrelation coefficient for the government spending shock rises from 0.80 to 0.89 and the autocorrelation of the preference shock rises from 0.06 to 0.20. As we will see later, these demand shocks will capture part of the trend in employment which in the full model is driven by the trends in the female labor supply and relative productivity shock.

The mode of the estimated growth rate of the technology shock is similar in the full model and simple model with labor supply shock, but 1.5 percentage points higher in the simple model without technology shock. Even with the small difference in estimates, the lower estimated growth rate of TFP in the simple model has large effects on the contribution of aggregate productivity growth to the growth of other variables over time. This is consistent with the notion that the rise in female labor supply and female relative productivity shock would be captured in the Solow residual and attributed to aggregate TFP growth in standard RBC model with no gender differences, as discussed in Section 3.1.3.

We now assess the role of the gender specific shocks and of the labor supply shock in affecting the estimated path of the common aggregate states. The estimated path for the aggregate states in the full model is presented in figure 15. No trends are apparent in any of the variables, and there are clear changes in the volatility of all the states over time. Specifically, the volatility of the investment shock μ, of the preference shock b, and of the government spending shock g all decline starting in the mid-1980s, while the volatility of the technology shock z rises substantially in the same period.

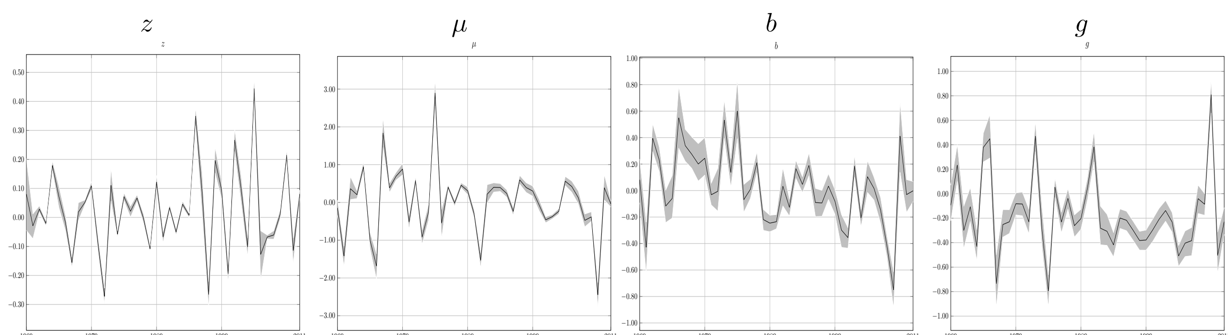


FIGURE 15: Full model. Estimated path of aggregate shocks. Annual data, 1969-2011

Turning to the simple model with a labor supply shock, we present the estimated path of the trend and cyclical component of this shock in figure 16. The trend component of the labor supply shock ϕ^T strongly declines until the early-1990s, while the cyclical component ϕ^C displays a decline in volatility starting in the mid-1980s. For the simple model without labor supply shock, the estimated value of the parameter for the disutility of labor is $\varphi = 0.20$, close to the average value of the realized labor supply shock in the version of the simple model that allows for that shock.

We now compare the estimated path of the aggregate states in the three versions of the model. We begin with the technology shock z, for which the estimated path for the three models is displayed in figure 17. In both versions of the simple model, there is a marked reduction in the volatility of the

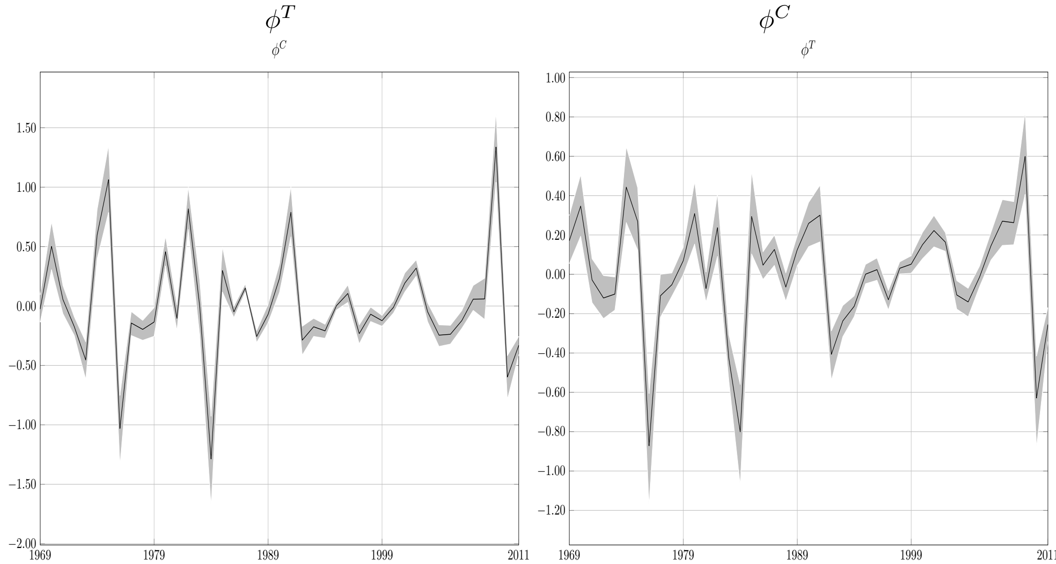
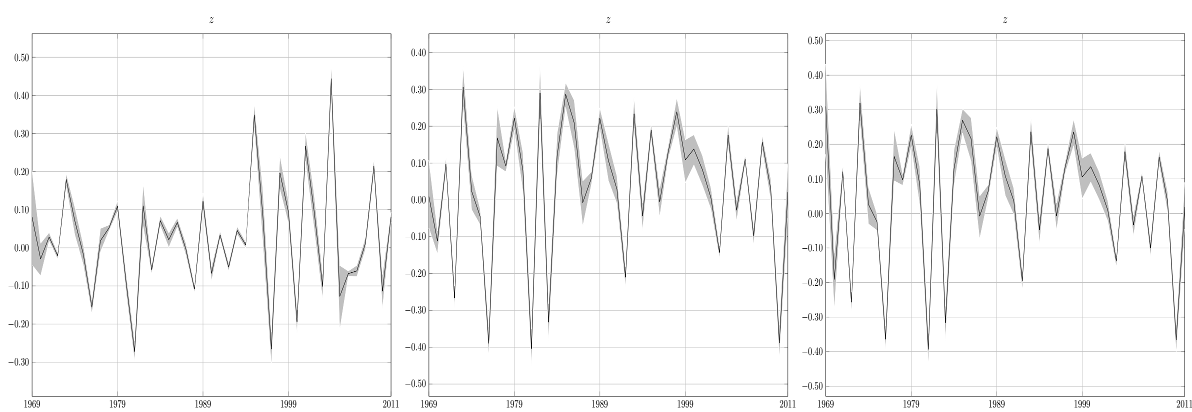


FIGURE 16: Simple model with labor supply shock. Estimated path of ϕ^T and ϕ^C. Annual data, 1969-2011

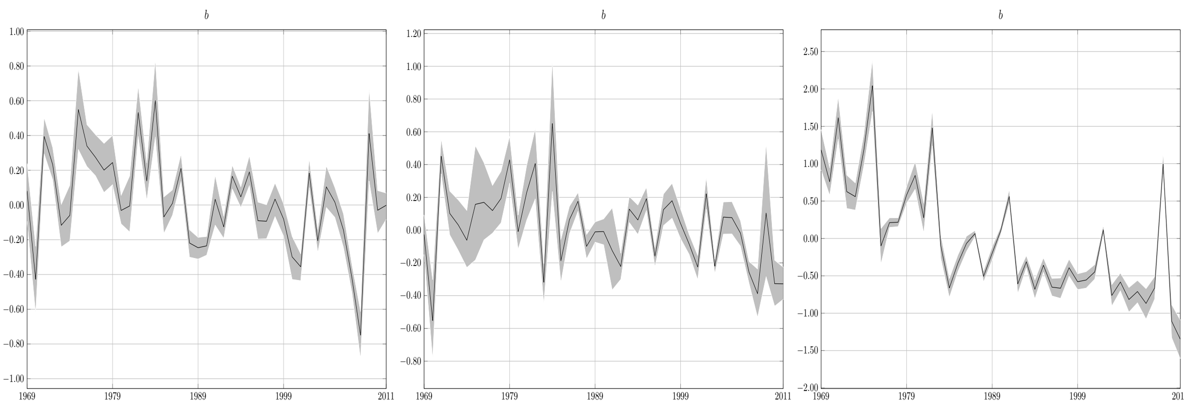
technology shock starting in the mid 1980s, whereas the full model displays an increase in volatility in the same period. This may be driven by the missing female specific productivity shock, which in the full model exhibits a decline in cyclical volatility starting in the mid 1980s. Absent the female relative productivity shock, this decline in volatility is captured by the technology shock. The estimated paths for the investment shock μ for the three models are displayed in figure 29 in Appendix C. For this shock, there are no major differences in the estimated paths across models.



(A) Full Model (B) Variable φ (C) Fixed φ

FIGURE 17: Model comparison, aggregate shocks: technology shock z. Sample period: 1969-2011

Figure 18 presents the estimated path of the preference shock b in the three versions of the model. There only minor differences between the full model and the simple model with a labor supply shock. Instead, for the simple model, the estimated path of b shows a marked trend decline starting in the early 1990s. A lower value of b tends to increase labor supply in the model as it reduces the disutility of labor in the current period relative to other periods. This suggests that in the absence of a trend decline in the labor supply shock, the rise in aggregate per capita hours can only be matched with a decline in the b shock, so that a *demand shock* absorbs the pattern of the missing labor supply shock. The estimated time path for g, displayed in figure 30 in Appedix C, displays a similar but muted pattern. In this case it is a rise in g that determines a rise in labor supply in the fixed ϕ simple model, since that causes a negative income effect.



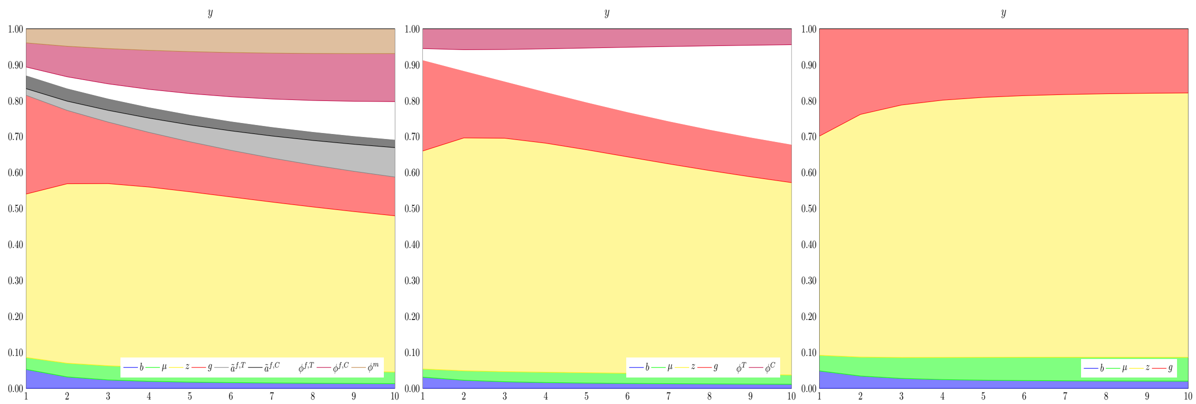
(A) Full Model (B) Variable φ (C) Fixed φ

FIGURE 18: Model comparison, aggregate shocks: preference shock b. Sample period: 1969-2011

4.2.1 Variance Decomposition

We now discuss the variance decomposition for the aggregate shocks in the three versions of the model. The results for output are displayed in figure 19. Whereas in the full model, at horizons over 5 years, the female relative productivity and labor supply shock combined account more of the variance of output than the technology shock, and more than twice the variance of investment than the investment shock, in the simple model, the labor supply shock only plays a sizable role in account for the variance of aggregate hours per capita. The trend component of the labor supply shock explains approximately 35% of the variance of aggregate hours at horizons greater than 5, while the cyclical component accounts for 3-10% at horizons smaller than 5. The trend and cyclical component of the labor supply shock combined explain less than 10% of the variance of output and consumption, and approximately 13% of the variance of investment, with this contribution stable across horizons. The government consumption shock plays a larger role, and accounts for close to 30% of the variance of output and up to 40$ of the variance of aggregate hours at horizon 1-2 years, though it does not matter for the variance of either consumption or investment.

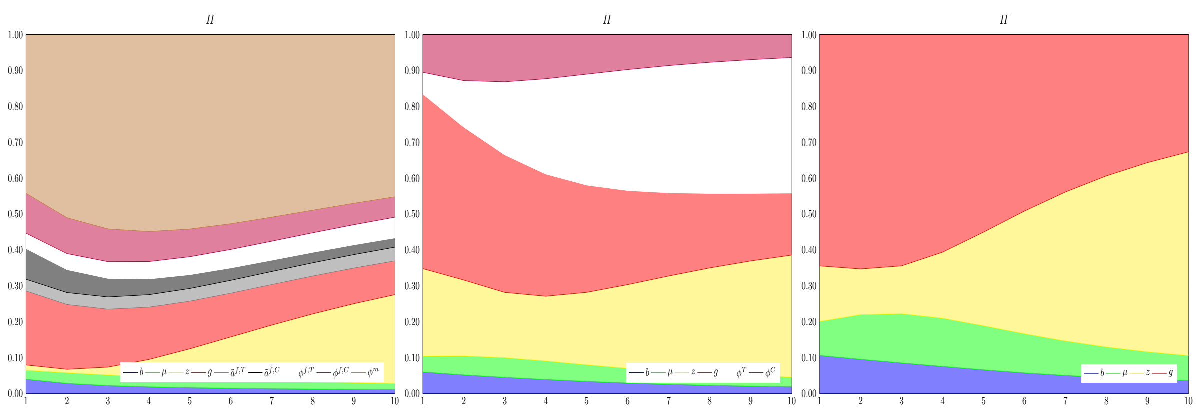
For the simple model without a labor supply shock, the government consumption shock fills in for the missing labor shock in explaining the variance of aggregate hours. It accounts for up to 65% of the variance of aggregate hours at horizons 1-4 years and approximately 35% at horizons greater than 5 years. The investment shock plays a larger role, and accounts for approximately 40% of the variance of investment, and very little of the variance of the other states. The preference shock b accounts for 15-18% of the variance of consumption and matters very little for the other states. A similar pattern holds for investment and capital utilization, displayed in figures **??** and **??** in Appendix C.



(A) Full Model (B) Variable φ (C) Fixed φ

FIGURE 19: Model comparison, variance decomposition: output y. Sample period: 1969-2011

Figure 20 displays the variance decomposition for aggregate per capita hours in the three version of the model. The most notable difference between the simple model and the full model is the much larger role of the government spending shock g, especially for the simple model with no labor supply shock. This pattern is consistent with g absorbing the missing labor supply and productivity trends in the basic models.



(A) Full Model (B) Variable φ (C) Fixed φ

FIGURE 20: Model comparison, variance decomposition: aggregate per capita hours H. Sample period: 1969-2011

The variance decomposition analysis is consistent with the estimated paths for the aggregate shocks in the different versions of the model. In the simple model, the demand shocks, both the preference and the government consumption shock, capture the trends that in the full model are

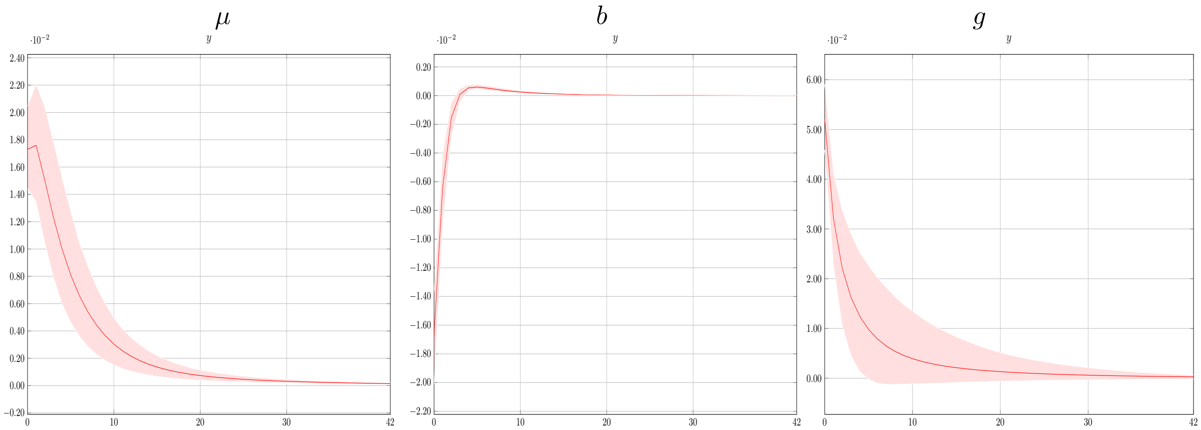


FIGURE 21: Impulse response, full model: output y to aggregate shocks. Sample period: 1969-2011

generated by the gender specific productivity and labor supply shocks. The absence of these shocks thus erroneously attributes importance to the these demand shocks in the behavior of aggregate output, hours. investment and capital utilization.

4.2.2 Impulse Responses

To gain further insight on the role of the gender specific shocks for aggregate variables, we examine the impulse response functions. In all cases, we consider responses to a 1 standard deviation rise in the variable of interest.

Figure 21 displays the response of output y to the aggregate shocks in the full model and figure 22 displays the response of y to the trend component of the gender specific shocks. The magnitude of the response on impact is very similar for the aggregate and gender specific shocks, though the response to the gender specific shocks is very persistent, which is not surprising given that we are looking at the trend component of these shocks. A positive shock to μ increases output by 0.024?? on impact, converging back to less than 0.002 by year 10. Shocks to b have a negligible and very short lived effect on output, while a positive shock to g raises output on impact by 0.06?? on impact, with the effect largely exhausted by year 8..

Turning to the gender specific shocks, a one standard deviation increase in female relative productivity raises output on impact by 0.02???by year 5, with the effect persisting at levels above 0.01 at year 25. A shock to $\tilde{\varphi}^{fT}$ decreases output which drops to a minimum of -0.018 by year 5 and then experiences a very slow recovery and never converges back to the initial level. The effect of a shock to φ^m is similar with a slightly large initial impact and a much shorter duration, due to the lower persistence of this shock.

Figures 23 and 24 display the response of aggregate per capita hours H to aggregate and gender specific shocks. The magnitude of the response on impact is slightly larger for the gender specific shocks than for the aggregate shocks. A positive shock toμ increases aggregate hours per capita by 0.02??? on impact, as it increases the marginal product of labor, but the effect dissipates after 8 years. A positive shock to b reduces hours, as it increases the utility cost of supplying labor,

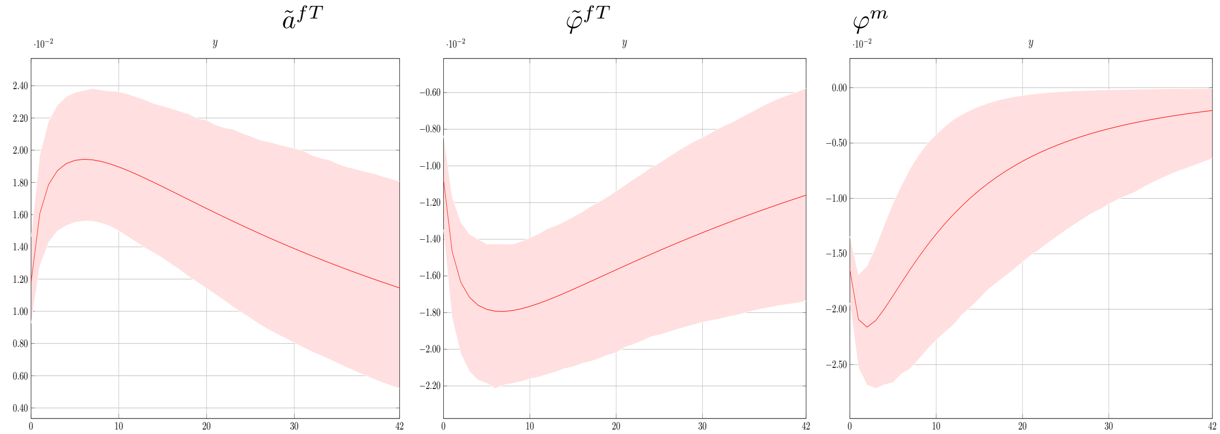


FIGURE 22: Impulse response, full model: output y to trend in gender specific shocks. Sample period: 1969-2011

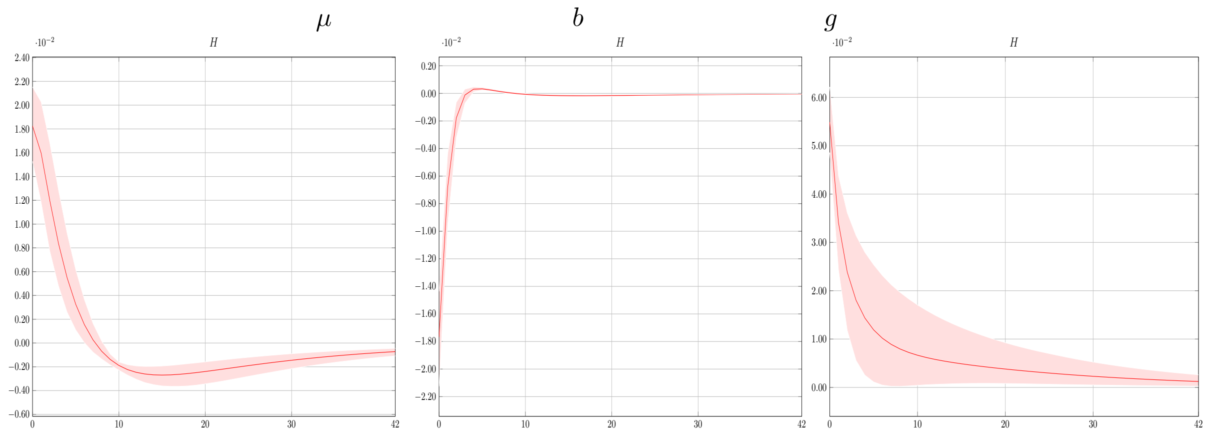


FIGURE 23: Impulse response, full model: output H to aggregate shocks. Sample period: 1969-2011

whereas a positive shock to g increases hours, due to the negative income effect.[13] The magnitude of the response to g is approximately 3 times larger than for the response to b.

The response of H to gender specific shocks is much larger in magnitude than to the aggregate shocks, and it is virtually permanent. An increase in female relative productivity reduces H by 0.022??? on impact, with the response stabilizing at -0.01??? by year 10. This negative effect is counterintuitive, and is driven by the fact that female hours rise while male hours decline and overall the higher productivity of labor reduces the demand for labor in equilibrium. A shock to $\tilde{\varphi}^{fT}$ increases aggregate hours on impact by 0.024???, with the effect stabilizing at 0.001??? by year 10. This response is due to the fact that female hours decline but male hours increase by more, leading to higher aggregate per capita hours as the male share of hours is larger than the female share. The intuition for the decline in aggregate per capita hours in response to a rise in φ^m is similar. Male hours decline while female hours rise, but the share of female hours is small, leading to an overall negative effects on aggregate hours. Moreover, the magnitude of the response is large, equal to -0.0075 on impact, because of the relatively large share of male hours. The response is less

[13] See [22] for an excellent discussion of the role of wealth effects in RBC models.

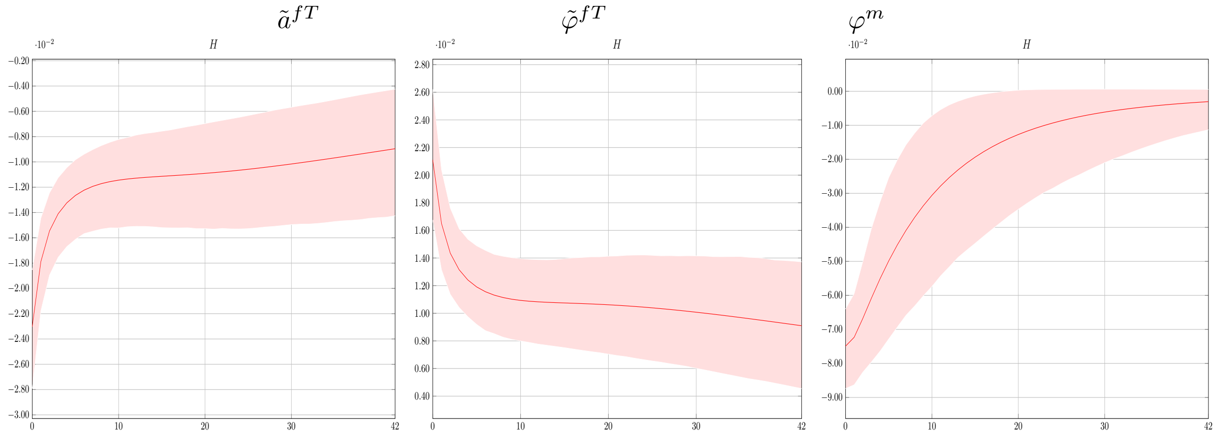


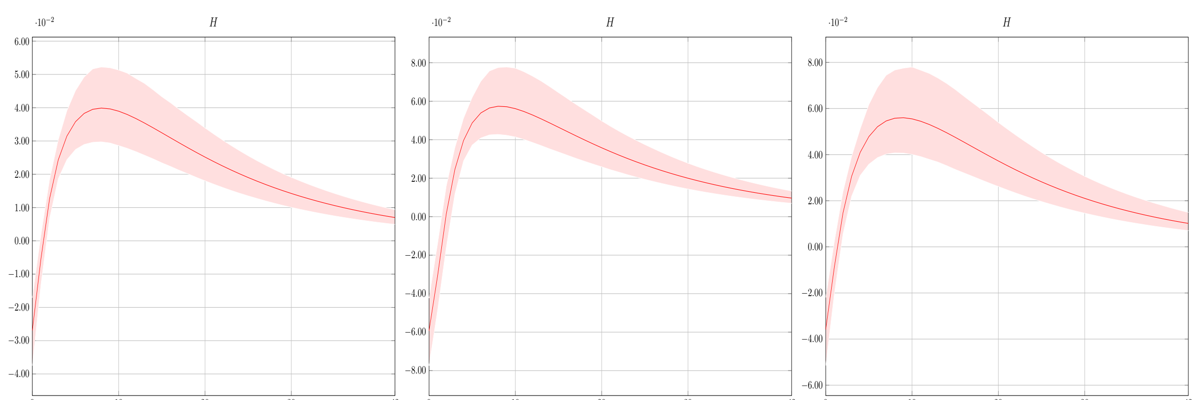
FIGURE 24: Impulse response, full model: output H to aggregate shocks. Sample period: 1969-2011

persistent than for the female labor supply shock.

We now compare the response of key variables to the aggregate shocks in the three versions of the model. Figure 25 displays the response of aggregate per capita hours to a technology shock in the three versions of the model. The response to a technology shock is larger in magnitude by about 30% in the two version of the simple model than in the full model, though the persistence of the response is similar across models. The impact response is negative, owing ot a negative income effect of higher productivity, and then turns positive as capital grows over time in response to higher TFP. The initial negative impact is only -0.03??? in the full model, and -0.06 and -0.04 in the two versions of the simple model, with and without the labor supply shock.

- Larger impact of z on H in basic models

H to z



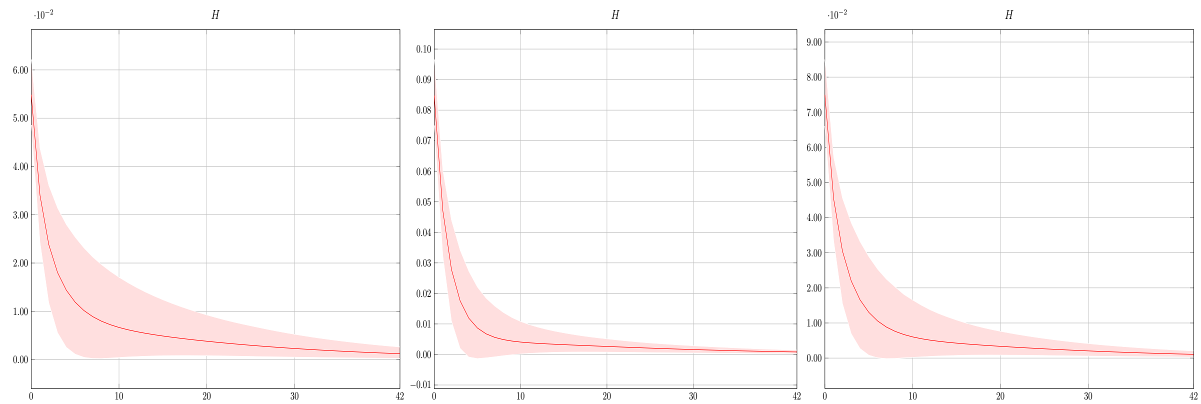
(A) Full Model (B) Variable φ (C) Fixed φ

FIGURE 25: Response of H to a shock to z. Sample period: 1969-2011

Figure 26 displays the response of H to a government consumption shock in the three versions of the model. The response is positive at all time horizons and once again, noticeably larger in the simple versions of the model. The impact effect in the full model is 0.05???, while it is 0.08 and 0.07 in the simple version of the model with and without labor supply shock.

- Larger impact of g on H in basic model with fixed φ

H to g



(A) Full Model (B) Variable φ (C) Fixed φ

FIGURE 26: Response of H to a shock to g. Sample period: 1969-2011

To summarize, the response of output is very similar in magnitude for aggregate shocks, such as the technology and government consumption shock, and the gender specific shocks, confirming their important role for the behavior of aggregate variables in the model. Additionally, the response of aggregate hours per capita is much larger for the gender specific shocks than for the aggregate shocks. Comparing the full to the simple versions of the model, we find that the impact of a technology and a government consumption shock on aggregate per capita hours is notably larger in the simple models than in the full model, suggesting an important interaction between gender specific and aggregate shocks in the behavior of aggregate per capita hours in the full version of the model.

4.3 Comparison of Time Periods

Tables 6 and 7 in Appendix B.1 present the parameter estimates for the 1969-1994 and 1995-2011 sub periods, which we refer to as the *transitional* and *steady state* period, respectively.

There are a number of notable difference in the estimates across the two sub periods. The autocorrelation coefficient for the female relative productivity and labor supply shocks are similar across time periods. However, the autocorrelation of the cyclical component of both the relative female productivity and the female labor supply shock is substantially lower in steady state period. The male labor supply shock, which does not have a persistent component, also displays lower autocorrelation during the steady state period. The standard deviation of the error term for the female relative productivity shock and the female labor supply shock is stable across periods for the trend component. However, for the cyclical component, he standard deviation of the error term for both female and male labor supply shock rises in steady state period. The standard deviation of the error term for the cyclical component of the female labor productivity shock is lower than for the men's labor supply shock in each sub period, but similar when estimated for the entire sample period. Turning to the aggregate shocks, the estimated autocorrelation of the investment shock is higher in the steady state period. For the technology shock, there is very little difference in the estimated autocorrelation coefficient, though the estimated standard deviation of the error term is higher in the steady state period, relative to the transition period.

We now examine the variance decompositions for the two sub periods, displayed in figures 27. The figure clearly shows that for the 1995-2011 sample period, there is a smaller role of the female and male labor supply shocks, and a larger role of the technology shock z in the variance decomposition of output. Interestingly, the female relative productivity shock plays a larger role in the variance decomposition of output in the steady state period. This is consistent with the growth accounting results in Section 3.1.3, which show a large contribution of female relative productivity growth to the Solow residual, average labor productivity and output in the mid 1990s. For aggregate per capita hours, we also observe a much larger role of the technology shocks for the variance decomposition in the later period, especially at longer horizons. As for output, we see a smaller fraction of variance explained by the trend component of female labor supply shock, but a larger fraction explained by the cyclical component. This is consistent with the evidence discussed in Section 2 that women's employment becomes more cyclical as labor force participation flattens in the 1990s. As for output, we see a larger role of the variance explained by the female relative productivity shock, for both the trend and cyclical components. A striking difference in the two sub periods is the large increase in the fraction of variance of aggregate per capita hours explained by the male labor supply shock at horizons shorter than 5 years, and the decline in this fraction for longer horizons. This result may be capturing the strong decline male employment during the 2007-2009 recession.

We conclude with the impulse response functions. Figure 28 shows the response of aggregate per capita hours to a technology shock and a government consumption shock in the two sub periods. The response to the technology shock is similar in pattern but about 20-25% larger in magnitude in the second period. The results are similar but magnified for the government consumption shock. Once again, the time path of the response is qualitatively similar in the two periods, but the magnitude of the response is two orders of magnitude greater in the second period compared to the first. This is consistent with the much larger share of the variance of aggregate per capita hours accounted for by the government consumption shock in the second period. We do not find sizable differences in the response to aggregate and gender specific variables to the gender specific shocks across periods.

To summarize, comparing the transition 1969-1994 period and the steady state 1995-2011 period, we find that there is smaller role of female shocks in 1995-2011 and larger role of z and ϕ^m for y, as reflected in the variance decomposition. A similar pattern holds for the other aggregate variables, except for aggregate per capita hours. For hours, the variance decomposition shows a smaller role of $\tilde{\varphi}^f$ in 1995-2011, larger role of the technology shock, the female relative productivity shock and th4e

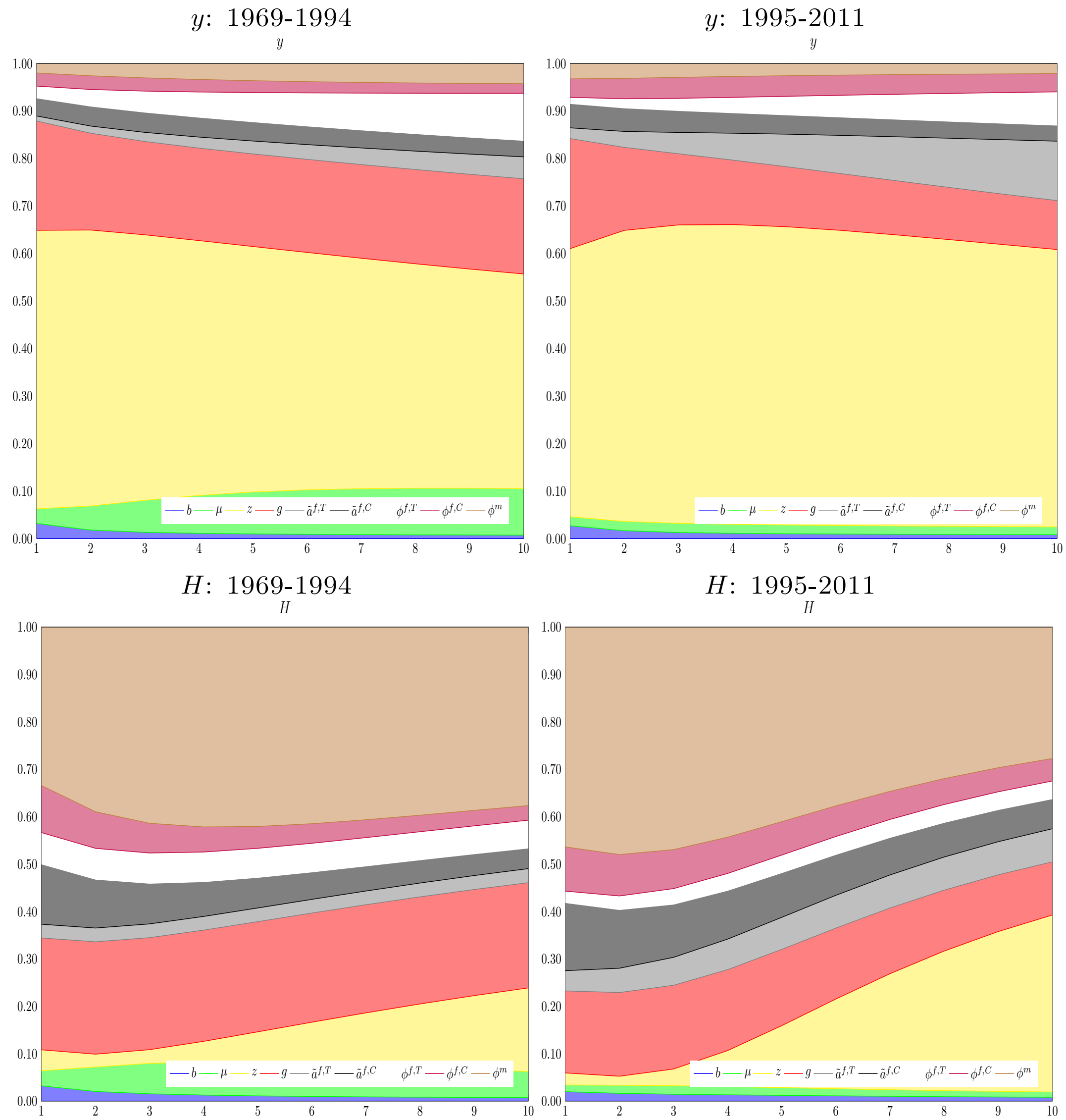


FIGURE 27: Variance decomposition of output and aggregate per capita hours, time comparison.

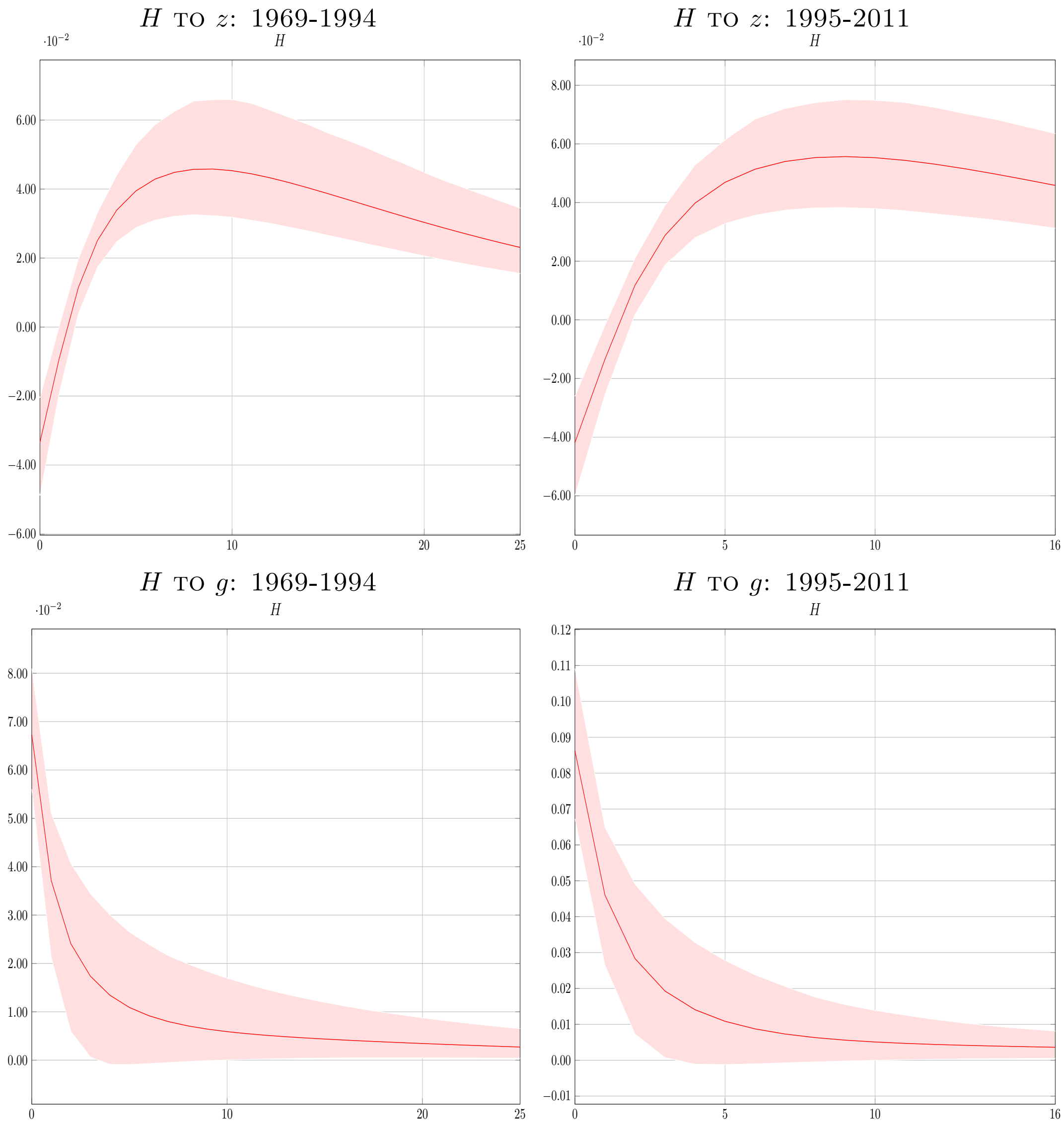


FIGURE 28: Response of aggregate per capita hours to a technology shock, time comparison.

male labor supply shock. The impulse response functions also suggest a larger role for aggregate shocks in the steady state 1995-2011 period. Specifically, there is a larger response of aggregate per capita hours to the technology shock z and and the government consumption shock g. This implies that a negative shock to these variables, corresponding to a supply side driven or an aggregate demand drive recession, would determine a larger and more persistent drop in aggregate per capita hours relative to the effect of similar shocks in the transitional 1969-1994 period, consistent with the emergence of jobless recoveries since the early 1990s.

5 Discussion

This paper builds a real DSGE model with gender differentiation in labor supply and productivity to augment the standard technology, investment, preference and government consumption shocks. The model is estimated with Bayesian methods over the 1969-2011 periods and used to assess the impact of the decline in convergence in hours and wages across men and women starting in the early 1990s on the properties of aggregate business cycles. We find that the gender specific shocks account for larger fraction of variance of output, hours and investment than the technology shock at medium and long horizons. By estimating version of the model that exclude the gender specific shocks, we show that the demand shocks, specifically, the preference and government consumption shock, absorb the trend in aggregate hours and wages not captured by the missing gender specific shocks. We also show that a version without of the model without gender specific shocks would estimate a decline in the variance of the technology shock starting in the mid 1980s, leading to the conclusion that a decline in the variance of the shock is the main source of the Great Moderation for that time period. However, including the gender specific shocks, there is a decline in the volatility of the cyclical component of these shocks and an *increase* in the volatility of the technology shock. This suggests that the decline in the volatility of the gender specific shocks is the main source of the decline in output and aggregate hours volatility observed starting in the mid 1980s.

Finally, we estimated the model in two periods, prior to 1994, when female participation was rising and women's wages were converging rapidly to men's, and 1995-2011, when these two phenomena stopped. We find that the gender specific shocks account for smaller fraction of the variance of aggregate variables and hours in 1995-2011, and the technology and government spending shock explain a larger fraction of the variance of output and hours. Moreover, these aggregate shock display a higher estimated persistence. Thus, technology and government consumption shocks induce larger and more persistent responses in output, investment and hours in the 1995-2011 period, consistent with the slow recovery in output and employment experienced in the 1991, 2001 and 2007-09 recession.

Taken together, these findings suggest that a DSGE model for the U.S. economy in the post-war period that does not include gender specific shocks to labor supply and productivity is misspecified, and leads to misleading inference on the source of economic fluctuations and on the impact of standard aggregate shocks.

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A Model Solution

A.1 Household and Firm Optimization

The household's first order necessary conditions for optimality are as follows:

- Consumption:

$$\Lambda_t = \frac{b_t}{C_t - \eta C_{t-1}} - \beta\eta E_t \frac{b_{t+1}}{C_{t+1} - \eta C_t}$$

  where $\Lambda_t$is the multiplier of the budget constraint;

- Physical capital $\left(\bar{K}_t\right)$:

$$\Phi_t = \beta E_t \left[\Lambda_{t+1}\left(r^k_{t+1}u_{t+1} - a(u_{t+1})\right)\right] + (1-\delta)\beta E_t \Phi_{t+1}$$

- Investment:

$$\Lambda_t = \Phi_t \mu_t \left[1 - S\left(\frac{I_t}{I_{t-1}}\right) - \frac{I_t}{I_{t-1}} S'\left(\frac{I_t}{I_{t-1}}\right)\right] + \beta E_t \left[\Phi_{t+1}\mu_{t+1}\left(\frac{I_{t+1}}{I_t}\right)^2 S'\left(\frac{I_{t+1}}{I_t}\right)\right]$$

- Utilization:

$$r^k_t = a'(u_t)$$

- Labor supply (H^j_t for $j = f, m$):

$$W^j_t = \frac{\varphi^j_t \left(H^j_t\right)^{\nu^j}}{\Lambda_t}. \tag{19}$$

The firms' first order necessary conditions are given by the following system of equations.

- Effective capital (K_t):

$$r^k_t = \alpha A^{1-\alpha}_t \left(\frac{L_t}{K_t}\right)^{1-\alpha};$$

- Demand for female labor $\left(H^f_t\right)$

$$W^f_t = (1-\alpha)\frac{Y_t}{H^f_t}\omega^f \left(\frac{\tilde{a}^f_t \left(H^f_t / H^f\right)}{L_t}\right)^{\rho}$$

- Demand for male labor (H^m_t):

$$W^m_t = (1-\alpha)\frac{Y_t}{H^m_t}\omega^m \left(\frac{\left(H^m_t / H^m\right)}{L_t}\right)^{\rho}$$

A.2 Characterizing the Solution for the Normalized Model

We adopt the following normalization to make the model stationary:

$$\begin{aligned} y &= Y/A \\ k &= K/A \\ \bar{k} &= \bar{K}/A \\ c &= C/A \\ i &= I/A \\ w^j &= W^j/A \\ \lambda &= \Lambda A \\ \phi &= \Phi A. \end{aligned}$$

We now rewrite the equilibrium conditions in terms of the normalized variables.

Households

- Consumption

$$\lambda_t = \frac{b_t e^{z_t}}{e^{z_t} c_t - \eta c_{t-1}} - \beta\eta E_t \frac{b_{t+1}}{e^{z_{t+1}} c_{t+1} - \eta c_t} \tag{20}$$

- Physical capital $\left(\bar{K}_t\right)$

$$\phi_t = \beta E_t \left\{ e^{-z_{t+1}} \lambda_{t+1} \left[r_{t+1}^k u_{t+1} - a\left(u_{t+1}\right) \right] \right\} + (1-\delta)\,\beta E_t \left(\phi_{t+1} e^{-z_{t+1}} \right) \tag{21}$$

- Investment

$$\begin{aligned} \lambda_t = \phi_t \mu_t & \left[1 - S\left(\frac{i_t}{i_{t-1}} e^{z_t} \right) - \frac{i_t}{i_{t-1}} e^{z_t} S'\left(\frac{i_t}{i_{t-1}} e^{z_t} \right) \right] \\ & + \beta E_t \left[\phi_{t+1} e^{-z_{t+1}} \mu_{t+1} \left(\frac{i_{t+1}}{i_t} e^{z_{t+1}} \right)^2 S'\left(\frac{i_{t+1}}{i_t} e^{z_{t+1}} \right) \right] \end{aligned} \tag{22}$$

- Utilization

$$r_t^k = a'(u_t) \tag{23}$$

- Definition of effective capital

$$k_t = u_t \bar{k}_{t-1} e^{-z_t} \tag{24}$$

- Physical capital accumulation

$$\bar{k}_t = (1-\delta) e^{-z_t} \bar{k}_{t-1} + \mu_t \left[1 - S\left(\frac{i_t}{i_{t-1}} e^{z_t} \right) \right] i_t \tag{25}$$

- Labor supply H_t^j for $j = f, m$

$$w_t^j = \frac{\varphi_t^j \left(H_t^j\right)^{\nu^j}}{\lambda_t} \tag{26}$$

Firms

- Production function

$$y_t = k_t^{\alpha} \left(L_t\right)^{1-\alpha} \tag{27}$$

- Labor input

$$L_t = \left[\omega^f \left(\tilde{a}_t^f \frac{H_t^f}{H^f}\right)^{\rho} + \omega^m \left(\frac{H_t^m}{H^m}\right)^{\rho}\right]^{1/\rho} \tag{28}$$

- Effective capital (K_t)

$$r_t^k = \alpha \left(\frac{L_t}{k_t}\right)^{1-\alpha} \tag{29}$$

- Female labor demand $\left(H_t^f\right)$

$$w_t^f = (1-\alpha) \frac{y_t}{H_t^f} \omega^f \left(\frac{\tilde{a}_t^f \left(H_t^f / H^f\right)}{L_t}\right)^{\rho} \tag{30}$$

- Male labor demand (H_t^m)

$$w_t^m = (1-\alpha) \frac{y_t}{H_t^m} \omega^m \left(\frac{\left(H_t^m / H^m\right)}{L_t}\right)^{\rho} \tag{31}$$

Resource Constraint and Summary

- Resource constraint

$$c_t + i_t + \frac{a(u_t)}{u_t} k_t = \frac{y_t}{g_t} \tag{32}$$

Equations (20)-(32) comprise a system of 13 dynamic equations in the 13 unknowns: $\left\{\lambda, c, \phi, r^k, u, i, k, \bar{k}, w^f, w^m, H^f, H^m, y, L\right\}$.

A.3 Steady State

The aggregate variables in the steady state for the rescaled version of the model are characterized by the following system of equations, using the normalization $L = 1$:

$$\begin{aligned} 1 &= \beta e^{\gamma} r^k + (1-\delta) \beta e^{\gamma} \\ r^k &= \frac{e^{\gamma}}{\beta} - (1-\delta) \end{aligned}$$

$$k=\left(\frac{\alpha}{r^{k}}\right)^{\frac{1}{1-\alpha}}$$

$$y=k^{\alpha}$$

$$\begin{aligned}
\overline{k} &= ke^{\gamma} \\
i &= \left[1-(1-\delta)e^{-\gamma}\right]\overline{k}
\end{aligned}$$

$$c=\frac{y}{g}-i$$

$$\lambda=\frac{1}{c}\frac{e^{\gamma}-\beta\eta}{e^{\gamma}-\eta}.$$

Equations 7, 8 and 9 provide four conditions to pin down wages and hours, with two extra degrees of freedom represented by the steady state values of the disutility of labor φ^{j}:

$$\begin{aligned}
w^{f} &= (1-\alpha)\frac{y}{H^{f}}\omega^{f}, \\
w^{m} &= (1-\alpha)\frac{y}{H^{m}}\omega^{m}, \\
w^{j} &= \frac{\varphi^{j}\left(H^{j}\right)^{\nu^{j}}}{\lambda},
\end{aligned}$$

for $j=f,\, m$. The value of φ's is not necessary to solve this model. However, it might be of interest to compute a value for the relative disutility of work that is compatible with the observed relative hours and wages. Given an observed value for average relative hours $h^{f}=\frac{H^{f}}{H^{m}}$, and normalizing $H^{m}=1$, we have:

$$\frac{w^{f}}{w^{m}}=\frac{\omega^{f}}{\omega^{m}}\left(\tilde{H}^{f}\right)^{-1},$$

from which we can finally pin down the relative disutility:

$$\tilde{\varphi}^{f}=\frac{w^{f}}{w^{m}}\left(\tilde{H}^{f}\right)^{-\nu^{f}}.$$

The value of φ^{m}compatible with the normalization $H^{m}=1$ is:

$$\varphi^{m}=(1-\alpha)\,y\omega^{m}\lambda.$$

A.4 Log Linear Approximation

We can now derive the model's log-linear approximation. Log-linear deviations from steady state are defined as follows, for a generic variable x_t with s.s. value x:

$$\hat{x}_t\equiv\log x_t-\log x,$$

except for $\hat{z}_t \equiv z_t - \gamma$. The set of state equations that will be used in the estimation comprise (33)-(45) derived below.

Households

- Consumption

$$\begin{aligned}(e^{\gamma} - \eta\beta)(e^{\gamma} - \eta)\hat{\lambda}_t = \eta\beta e^{\gamma} E_t \hat{c}_{t+1} - \left(e^{2\gamma} + \eta^2\beta\right)\hat{c}_t + \eta e^{\gamma}\hat{c}_{t-1} \\ + \eta e^{\gamma}(\beta\rho_z - 1)\hat{z}_t + (e^{\gamma} - \eta\beta\rho_b)(e^{\gamma} - \eta)\hat{b}_t \quad (33)\end{aligned}$$

- Physical capital $\left(\bar{K}_t\right)$

$$\hat{\phi}_t = (1-\delta)\beta e^{-\gamma} E_t\left(\hat{\phi}_{t+1} - \hat{z}_{t+1}\right) + \left(1 - (1-\delta)\beta e^{-\gamma}\right) E_t\left[\hat{\lambda}_{t+1} - \hat{z}_{t+1} + \hat{r}^k_{t+1}\right] \quad (34)$$

- Investment

$$\hat{\lambda}_t = \hat{\phi}_t + \hat{\mu}_t - e^{2\gamma}\zeta(\hat{\imath}_t - \hat{\imath}_{t-1} + \hat{z}_t) + \beta e^{2\gamma}\zeta E_t\left[\hat{\imath}_{t+1} - \hat{\imath}_t + \hat{z}_{t+1}\right] \quad (35)$$

- Utilization

$$\hat{r}^k_t = \chi\hat{u}_t \quad (36)$$

- Definition of effective capital

$$\hat{k}_t = \hat{u}_t + \hat{\bar{k}}_{t-1} - \hat{z}_t \quad (37)$$

- Physical capital accumulation

$$\hat{\bar{k}}_t = (1-\delta)e^{-\gamma}\left(\hat{\bar{k}}_{t-1} - \hat{z}_t\right) + \left(1 - (1-\delta)e^{-\gamma}\right)(\hat{\mu}_t + \hat{\imath}_t) \quad (38)$$

- Labor supply ($H^j_t$for $j = f, m$)

$$\hat{w}^j_t = \hat{\varphi}^j_t + \nu^j \hat{H}^j_t - \hat{\lambda}_t \quad (39)$$

Firms

- Production function

$$\hat{y}_t = \alpha\hat{k}_t + (1-\alpha)\hat{L}_t \quad (40)$$

- Labor input

$$\hat{L}_t = \omega^f\left(\hat{\tilde{a}}^f_t + \hat{H}^f_t\right) + \omega^m \hat{H}^m_t \quad (41)$$

- Return to capital

$$\hat{r}^k_t = (1-\alpha)\left(\hat{L}_t - \hat{k}_t\right) \quad (42)$$

- Female labor demand $\left(H_t^f\right)$

$$\hat{w}_t^f = \hat{y}_t + (\rho - 1)\,\hat{H}_t^f + \rho\hat{\tilde{a}}_t^f - \rho\hat{L}_t \tag{43}$$

- Male labor demand (H_t^m)

$$\hat{w}_t^m = \hat{y}_t + (\rho - 1)\,\hat{H}_t^m - \rho\hat{L}_t \tag{44}$$

Resource Constraint

- Resource constraint

$$\frac{c}{y}\hat{c}_t + \frac{i}{y}\hat{\imath}_t + \frac{r^k k}{y}\hat{u}_t = \frac{1}{g}\hat{y}_t - \frac{1}{g}\hat{g}_t \tag{45}$$

A.5 Shocks

Following [25], we normalize the intertemporal preference shock as:

$$\hat{b}_t^* = \frac{(e^\gamma - \eta)\,(e^\gamma - \eta\beta\rho_b)\,(1-\rho_b)}{e^{2\gamma} + \eta^2\beta + \eta e^\gamma}\hat{b}_t$$

so as to make the coefficient on consumption in the Euler equation equal to one. The Euler equation pricing a real one-period bond with interest rate r_t, which we did not consider explicitly, reads:

$$\hat{\lambda}_t = E_t\left[\hat{\lambda}_{t+1} - \hat{z}_{t+1}\right] + \hat{r}_t$$

and substituting equation (33), we obtain:

$$\begin{aligned}
\frac{e^{2\gamma} + \eta^2\beta + \eta e^\gamma}{(e^\gamma - \eta\beta)\,(e^\gamma - \eta)}\hat{c}_t + (...) \quad &= \quad (...) + \frac{(e^\gamma - \eta\beta\rho_b)\,(1-\rho_b)}{e^\gamma - \eta\beta}\hat{b}_t \\
\hat{c}_t + (...) \quad &= (...) + \quad \frac{(e^\gamma - \eta)\,(e^\gamma - \eta\beta\rho_b)\,(1-\rho_b)}{e^{2\gamma} + \eta^2\beta + \eta e^\gamma}\hat{b}_t.
\end{aligned}$$

Using this normalization, the resulting set of exogenous shocks in the model is summarized in 4.

A.6 Observation Equations

We adopt the following observation equations, where all series are measured in deviations from their mean over the period of the estimation.

Table 4: Exogenous Shocks

$\hat{b}_t^*$	$= \rho_b \hat{b}_{t-1}^* + \varepsilon_{b,t}$
$\hat{\mu}_t$	$= \rho_\mu \hat{\mu}_{t-1} + \varepsilon_{\mu,t}$
$\hat{z}_t$	$= \rho_z \hat{z}_{t-1} + \varepsilon_{z,t}$
$\hat{g}_t$	$= \rho_g \hat{g}_{t-1} + \varepsilon_{g,t}$
$\hat{\tilde{a}}_t^f$	$= \hat{\tilde{a}}_t^{fT} + \hat{\tilde{a}}_t^{fC}$
$\hat{\tilde{a}}_t^{fT}$	$= \rho_{\tilde{a}^{fT}} \hat{\tilde{a}}_{t-1}^{fT} + \varepsilon_{\tilde{a}^{fT},t}$
$\hat{\tilde{a}}_t^{fC}$	$= \rho_{\tilde{a}^{fC}} \hat{\tilde{a}}_{t-1}^{fC} + \varepsilon_{\tilde{a}^{fC},t}$
$\hat{\tilde{\varphi}}_t^f$	$= \hat{\tilde{\varphi}}_t^{fT} + \hat{\tilde{\varphi}}_t^{fC}$
$\hat{\tilde{\varphi}}_t^{fT}$	$= \rho_{\tilde{\varphi}^{fT}}^T \hat{\tilde{\varphi}}_{t-1}^{fT} + \varepsilon_{\tilde{\varphi}^{fT},t}^T$
$\hat{\tilde{\varphi}}_t^{fC}$	$= \rho_{\tilde{\varphi}^{fC}}^T \hat{\tilde{\varphi}}_{t-1}^{fC} + \varepsilon_{\tilde{\varphi}^{fC},t}$
$\hat{\varphi}_t^m$	$= \rho_{\varphi^m} \hat{\varphi}_{t-1}^m + \varepsilon_{\varphi^m,t}$

Table 5: Observation Equations

log GDP Growth	$= \hat{y}_t - \hat{y}_{t-1} + \hat{z}_t$
log Consumption Growth	$= \hat{c}_t - \hat{c}_{t-1} + \hat{z}_t$
log Investment Growth	$= \hat{i}_t - \hat{i}_{t-1} + \hat{z}_t$
log Hours, Men	$= \hat{H}_t^m$
log Hours, Relative	$= \hat{H}_t^f - \hat{H}_t^m$
log Labor Share, Men	$= \hat{w}_t^m + \hat{H}_t^m - \hat{y}_t$

B Full Model: Additional Results

B.1 Estimates for Sub Periods

Table 6: Full model. Sample period: 1969-1994.

		Prior					Posterior				
	Dist	10%	Median	90%		Mode	Mean	SE	10%	Median	90%
γ	N	3.0000	0.4616	0.5000	0.5384	0.5000	0.5000	0.0272	0.4671	0.5039	0.5376
χ	G	2.0000	3.7689	4.9335	6.3167	5.1849	5.1849	1.0981	4.0431	5.4350	6.7793
η	B	1.0000	0.3701	0.5000	0.6299	0.4406	0.4406	0.0840	0.3220	0.4300	0.5405
ζ	G	2.0000	1.5236	2.5776	4.0345	2.3021	2.3021	0.8913	1.9722	2.8293	4.1471
ρ_b	B	1.0000	0.3205	0.6143	0.8574	0.1090	0.1090	0.0829	0.0590	0.1459	0.2724
ρ_μ	B	1.0000	0.3205	0.6143	0.8574	0.3449	0.3449	0.1573	0.1697	0.3572	0.5805
ρ_z	B	1.0000	0.1426	0.3857	0.6795	0.2245	0.2245	0.1642	0.0925	0.2766	0.5355
ρ_g	B	1.0000	0.3205	0.6143	0.8574	0.8338	0.8338	0.1894	0.4445	0.7779	0.9148
$\rho_{\tilde{a}^{f,T}}$	B	1.0000	0.9599	0.9836	0.9954	0.9869	0.9869	0.0167	0.9541	0.9803	0.9932
$\rho_{\tilde{a}^{f,C}}$	B	1.0000	0.2306	0.5000	0.7694	0.7282	0.7282	0.1732	0.4115	0.6697	0.8643
$\rho_{\phi^{f,T}}$	B	1.0000	0.9599	0.9836	0.9954	0.9884	0.9884	0.0154	0.9570	0.9813	0.9931
$\rho_{\phi^{f,C}}$	B	1.0000	0.2306	0.5000	0.7694	0.5846	0.5846	0.1924	0.2887	0.5564	0.8042
ρ_{ϕ^m}	B	1.0000	0.3205	0.6143	0.8574	0.8537	0.8537	0.1458	0.5499	0.7897	0.9119
σ_b	IG1	4.0000	0.0260	0.0600	0.1880	0.0193	0.0193	0.0038	0.0165	0.0205	0.0261
σ_μ	IG1	4.0000	0.1470	0.3250	0.9390	0.2031	0.2031	0.0761	0.1718	0.2484	0.3601
σ_z	IG1	4.0000	0.3760	0.7480	0.9990	0.1971	0.1971	0.0222	0.1709	0.1985	0.2295
σ_g	IG1	4.0000	0.1470	0.3250	0.9390	0.0854	0.0854	0.0110	0.0736	0.0857	0.1027
$\sigma_{\tilde{a}^{f,T}}$	IG1	4.0000	0.0530	0.1220	0.3760	0.0513	0.0513	0.0105	0.0438	0.0555	0.0711
$\sigma_{\tilde{a}^{f,C}}$	IG1	4.0000	0.1130	0.2530	0.7520	0.0778	0.0778	0.0116	0.0686	0.0812	0.0979
$\sigma_{\phi^{f,T}}$	IG1	4.0000	0.0530	0.1220	0.3760	0.0573	0.0573	0.0117	0.0477	0.0618	0.0775
$\sigma_{\phi^{f,C}}$	IG1	4.0000	0.1130	0.2530	0.7520	0.0889	0.0889	0.0154	0.0769	0.0932	0.1147
σ_{ϕ^m}	IG1	4.0000	0.1470	0.3250	0.9390	0.1071	0.1071	0.0181	0.0917	0.1127	0.1391

Posterior log density at mode: 194.9236. Source: Author's calculations from CPS and BLS data.

Table 7: Full model. Sample period: 1995-2011.

		Prior						Posterior			
	Dist	10%	Median	90%		Mode	Mean	SE	10%	Median	90%
γ	N	3.0000	0.4616	0.5000	0.5384	0.5000	0.5000	0.0306	0.4599	0.4991	0.5401
χ	G	2.0000	3.7689	4.9335	6.3167	5.0428	5.0428	1.0326	3.8531	5.0718	6.5319
η	B	1.0000	0.3701	0.5000	0.6299	0.4507	0.4507	0.0836	0.3225	0.4264	0.5414
ζ	G	2.0000	1.5236	2.5776	4.0345	2.9350	2.9350	0.9844	2.2949	3.2011	4.7363
ρ_b	B	1.0000	0.3205	0.6143	0.8574	0.1339	0.1339	0.0871	0.0735	0.1646	0.2987
ρ_μ	B	1.0000	0.3205	0.6143	0.8574	0.4425	0.4425	0.1595	0.2625	0.4640	0.6791
ρ_z	B	1.0000	0.1426	0.3857	0.6795	0.1943	0.1943	0.1519	0.0980	0.2822	0.5027
ρ_g	B	1.0000	0.3205	0.6143	0.8574	0.8288	0.8288	0.1674	0.4670	0.7327	0.8857
$\rho_{\tilde{a}^{f,T}}$	B	1.0000	0.9599	0.9836	0.9954	0.9857	0.9857	0.0149	0.9568	0.9798	0.9930
$\rho_{\tilde{a}^{f,C}}$	B	1.0000	0.2306	0.5000	0.7694	0.6103	0.6103	0.1757	0.3274	0.5701	0.7925
$\rho_{\phi^{f,T}}$	B	1.0000	0.9599	0.9836	0.9954	0.9850	0.9850	0.0170	0.9522	0.9789	0.9924
$\rho_{\phi^{f,C}}$	B	1.0000	0.2306	0.5000	0.7694	0.5306	0.5306	0.1936	0.2571	0.5256	0.7842
ρ_{ϕ^m}	B	1.0000	0.3205	0.6143	0.8574	0.6419	0.6419	0.1894	0.3230	0.5971	0.8361
σ_b	IG1	4.0000	0.0260	0.0600	0.1880	0.0220	0.0220	0.0057	0.0185	0.0234	0.0305
σ_μ	IG1	4.0000	0.1470	0.3250	0.9390	0.1758	0.1758	0.0522	0.1418	0.1929	0.2700
σ_z	IG1	4.0000	0.3760	0.7480	0.9990	0.2342	0.2342	0.0364	0.2020	0.2454	0.2953
σ_g	IG1	4.0000	0.1470	0.3250	0.9390	0.1009	0.1009	0.0195	0.0882	0.1093	0.1398
$\sigma_{\tilde{a}^{f,T}}$	IG1	4.0000	0.0530	0.1220	0.3760	0.0609	0.0609	0.0157	0.0495	0.0652	0.0897
$\sigma_{\tilde{a}^{f,C}}$	IG1	4.0000	0.1130	0.2530	0.7520	0.0998	0.0998	0.0217	0.0857	0.1059	0.1401
$\sigma_{\phi^{f,T}}$	IG1	4.0000	0.0530	0.1220	0.3760	0.0620	0.0620	0.0164	0.0537	0.0717	0.0957
$\sigma_{\phi^{f,C}}$	IG1	4.0000	0.1130	0.2530	0.7520	0.1056	0.1056	0.0217	0.0878	0.1109	0.1428
σ_{ϕ^m}	IG1	4.0000	0.1470	0.3250	0.9390	0.1267	0.1267	0.0266	0.1094	0.1383	0.1750

Posterior log density at mode: 126.8593. Source: Author's calculations from CPS and BLS data.

C Estimates for Simple Model

C.1 Simple Model with Labor Supply Shock

Table 8: Estimated parameters. Simple model with labor supply shock.

	Prior							Posterior			
	Dist	10%	Median	90%		Mode	Mean	SE	10%	Median	90%
γ	N	3.0000	0.4616	0.5000	0.5384	0.5000	0.5000	0.0293	0.4587	0.4950	0.5356
χ	G	2.0000	3.7689	4.9335	6.3167	5.3219	5.3219	0.9941	4.2256	5.4383	6.8450
η	B	1.0000	0.3701	0.5000	0.6299	0.6095	0.6095	0.0741	0.5161	0.6126	0.7052
ζ	G	2.0000	1.5236	2.5776	4.0345	2.2361	2.2361	0.6606	1.9375	2.6423	3.5364
ρ_b	B	1.0000	0.3205	0.6143	0.8574	0.0500	0.0500	0.0425	0.0303	0.0718	0.1397
ρ_μ	B	1.0000	0.3205	0.6143	0.8574	0.2776	0.2776	0.1279	0.1586	0.3149	0.4950
ρ_z	B	1.0000	0.1426	0.3857	0.6795	0.2311	0.2311	0.1478	0.1052	0.2857	0.5007
ρ_g	B	1.0000	0.3205	0.6143	0.8574	0.7868	0.7868	0.1388	0.5222	0.7321	0.8734
ρ_{ϕ^T}	B	1.0000	0.9599	0.9836	0.9954	0.9859	0.9859	0.0163	0.9538	0.9780	0.9931
ρ_{ϕ^C}	B	1.0000	0.2306	0.5000	0.7694	0.3292	0.3292	0.1612	0.1558	0.3437	0.5813
ρ_{ϕ^m}	IG1	4.0000	0.0260	0.0600	0.1880	0.0148	0.0148	0.0021	0.0134	0.0156	0.0191
σ_b	IG1	4.0000	0.1470	0.3250	0.9390	0.1688	0.1688	0.0517	0.1352	0.1874	0.2654
σ_μ	IG1	4.0000	0.3760	0.7480	0.9990	0.1622	0.1622	0.0138	0.1593	0.1719	0.1944
σ_z	IG1	4.0000	0.1470	0.3250	0.9390	0.0684	0.0684	0.0063	0.0660	0.0718	0.0825
σ_g	IG1	4.0000	0.0530	0.1220	0.3760	0.0539	0.0539	0.0167	0.0467	0.0625	0.0862
σ_{ϕ^T}	IG1	4.0000	0.1130	0.2530	0.7520	0.1192	0.1192	0.0354	0.0940	0.1274	0.1849

Posterior log density at mode: 215.8760. Annual data, 1969-2011.

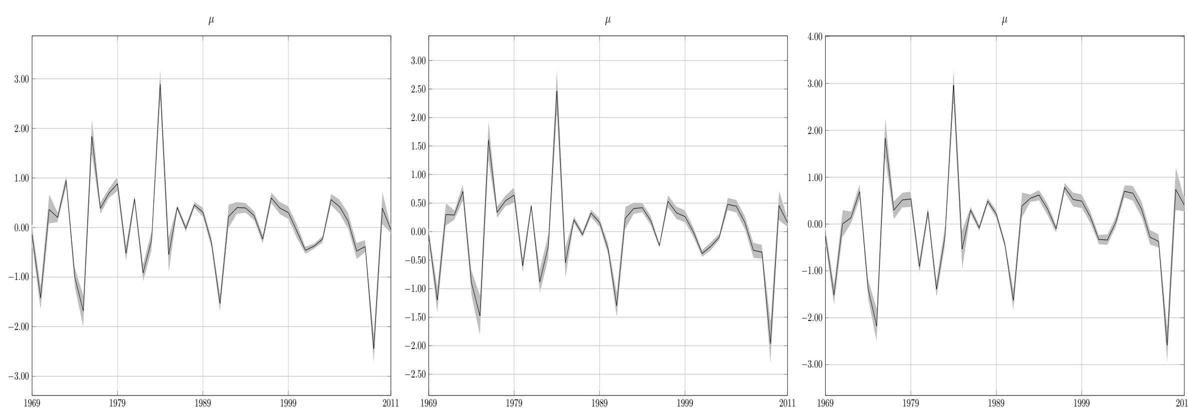
C.2 Simple Model Without Labor Supply Shock

Table 9: Estimated parameters. Simple model without labor supply shock.

	Prior					Posterior					
	Dist	10%	Median	90%		Mode	Mean	SE	10%	Median	90%
γ	N	3.0000	0.4616	0.5000	0.5384	0.5000	0.5000	0.0313	0.4611	0.5014	0.5411
χ	G	2.0000	3.7689	4.9335	6.3167	5.2960	5.2960	0.9057	4.4086	5.4402	6.6721
η	B	1.0000	0.3701	0.5000	0.6299	0.4403	0.4403	0.0939	0.2732	0.3957	0.5208
ζ	G	2.0000	1.5236	2.5776	4.0345	2.4815	2.4815	0.8828	2.0246	2.9855	4.2549
ρ_b	B	1.0000	0.3205	0.6143	0.8574	0.1597	0.1597	0.0930	0.0830	0.1916	0.3217
ρ_μ	B	1.0000	0.3205	0.6143	0.8574	0.2982	0.2982	0.1194	0.1689	0.3072	0.4805
ρ_z	B	1.0000	0.1426	0.3857	0.6795	0.2163	0.2163	0.1571	0.1023	0.2861	0.5261
ρ_g	B	1.0000	0.3205	0.6143	0.8574	0.8161	0.8161	0.1090	0.6230	0.7899	0.8981
σ_b	IG1	4.0000	0.0260	0.0600	0.1880	0.0181	0.0181	0.0029	0.0155	0.0189	0.0227
σ_μ	IG1	4.0000	0.1470	0.3250	0.9390	0.2308	0.2308	0.0778	0.1948	0.2654	0.3813
σ_z	IG1	4.0000	0.3760	0.7480	0.9990	0.1613	0.1613	0.0133	0.1592	0.1709	0.1925
σ_g	IG1	4.0000	0.1470	0.3250	0.9390	0.0682	0.0682	0.0064	0.0660	0.0716	0.0815
ϕ	N	3.0000	-0.0563	0.2000	0.4563	0.2000	0.2000	0.0640	0.0820	0.1558	0.2423

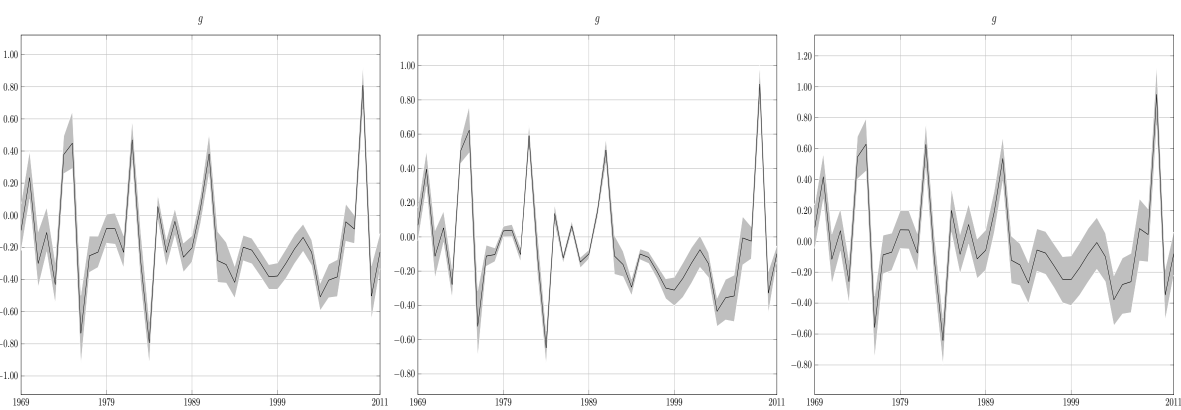
Posterior log density at mode: 217.0082. Annual data, 1969-2011.

C.3 Model Comparison: Aggregate Shocks



(A) Full Model (B) Variable φ (C) Fixed φ

Figure 29: Model comparison, aggregate shocks: investment shock μ. Sample period: 1969-2011



(A) Full Model (B) Variable ϕ (C) Fixed ϕ

Figure 30: Model comparison, aggregate shocks: preference shock g. Sample period: 1969-2011

C.4 Model Comparison: Variance Decomposition

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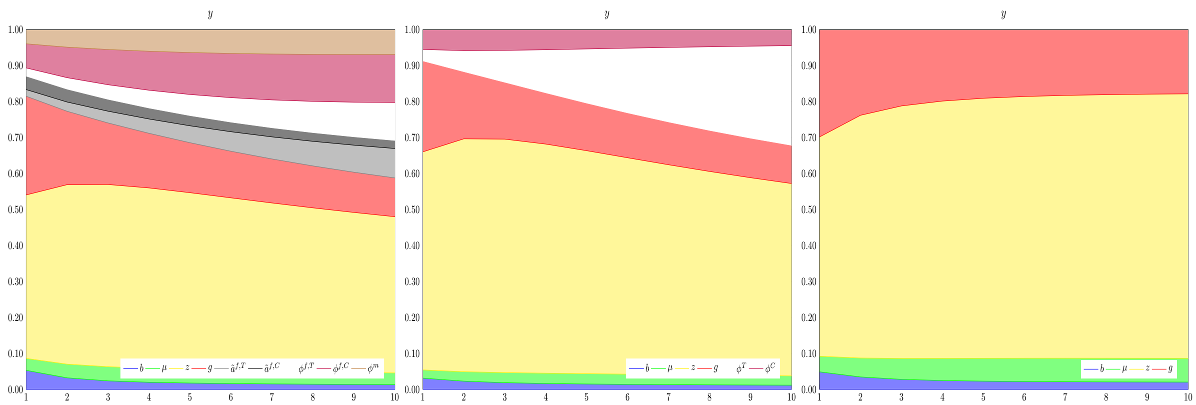

(A) Full Model (B) Variable φ (C) Fixed φ

Sample period: 1969-2011